PAPER

Constrained Adaptive Constant Modulus RLS Algorithm for Blind DS-CDMA Multiuser Receiver under Time-Varying Channels

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SUMMARY The performance of the blind multiuser detector for a DS-CDMA system with linearly constrained constant modulus (LCCM) criterion is known to highly depend on the exact knowledge of the desired user amplitude; it is usually not available at receiver end. In this paper, we propose a novel LC adaptive CM RLS (LC-ACM-RLS) algorithm to adaptively implement the optimal solution of the LCCM receiver, and to track the desired user's amplitude, simultaneously. From computer simulations, we verify the superiority of the new proposed algorithm over the conventional LCCM-RLS algorithm for multiple access interference (MAI) suppression. Also, for time-varying channel during the adaptation processes, if the amplitude of desired user is not available and varies with time, such as hand-off and Rayleigh fading environments, we show that the proposed LC-ACM-RLS algorithm has better tracking capability compared with the conventional approaches.

key words: *DS-CDMA multiuser detector, constant modulus criterion, linearly constrained RLS algorithm, multiple access interference, tracking capability*

1. Introduction

The direct sequence code division multiple access (DS-CDMA) is one of the most promising multiplexing technologies; it attracts more interests with its known widely applications [1]. It is also a core technology used in the wide-band CDMA (WCDMA) system for the third generation (3G) wireless communication systems. Due to the diverse phenomena of the practical channels, in the CDMA systems, the incomplete orthogonality of the spreading codes between users may occur and thus introduce the so-called multiple access interference (MAI). Usually, the near-far problem exists, when the interfering users are assigned powers much higher than the desired user. Such that the system performance might degrade, dramatically, and thus limits the system capacity. To circumvent the above-mentioned problems many adaptive multiuser detectors, based on the minimum mean square error (MMSE) [2], [3] and the minimum output energy (MOE) criteria subject to certain constraints [4], [5] have been proposed. In general, the MMSE approach has better performance achievement over the MOE approach, however it suffers from the need for training sequences.

To implement the blind multiuser detector the linearly constrained minimum variance (LCMV) [4], [5], which is the constrained version of MOE, has been suggested. Unfortunately, as indicated in [6], [11] the LCMV approach is very sensitive to inaccuracies in the acquisition of the desired user timing and user spreading code. Further, the LCMV-based receiver exhibits high sensitivity to the channel mismatch caused by the unreliable estimation. To deal with this problem the constant modulus (CM) criterion was considered in [6]–[14]. Basically, CM is a property-restoration approach that exploits the fact that the transmitted waveforms of communication signals are commonly found with certain invariant properties, e.g., constant envelopes. It suffers from the capturing effect when the power of interfering user is much higher than the desired user; it captures the interfering user instead of the desired user. To avoid this effect, the same constraint as imposed in the LCMV approach has to be employed associated with the CM criterion, and is termed as the LCCM criterion. It turns out to be very robust to code and timing inaccuracies, and the phenomenon of the desired signal cancellation can be avoided. If the desired user amplitude were selected properly under some specific conditions, with the LCCM approach the effect of MAI could be completely removed [7]–[10]. Since in practical applications the exact information of the desired user amplitude is not available in the receiver end, especially when channel is time-variant (e.g., hand-off or Rayleigh fading channel). Under such circumstance, we are not able to attain the desired performance with the conventional LCCM approach.

To circumvent the above-mentioned problem, in [17] the LC differential CM algorithm (LC-DCMA) was proposed to avoid the disadvantage of the conventional LCCM approach. With this approach, it requires no knowledge about the desired user amplitude. The basic idea of this approach is to use the information of power of past output signal as the reference signal. After that, the stochastic gradient method, having slow convergence rate, was used to implement the optimal weight vector. Unfortunately, it may not perform well under the Rayleigh fading channel, as shown in the simulation section. In this paper, we propose a novel linearly constrained adaptive constant modulus RLS (LC-ACM-RLS) algorithm for blind multiuser detector of DS-CDMA system, to deal with the MAI suppression, under time-varying channel. Without having the exact knowledge of the desired user amplitude, it can be used to adaptively implement the optimal solution of the LCCM receiver. With the new proposed LC-ACM-RLS algorithm, the amplitude variation of the desired user, due to changing

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characteristics of the channel, can be tracked, adaptively. Thus, better performance achievement, in terms of output signal-to-interference-plus-noise ratio (SINR) and bit error rate (BER), over the conventional LCCM-LMS and LCCM-RLS algorithms [6]–[14] can be expected.

2. System Model Description

As an introduction, let us consider an equivalent baseband BPSK DS-CDMA receiver, with K users, where the received signal is given by

$$r(t) = \sum_{k=1}^{K} A_k\beta_k(t) \sum_{i=-\infty}^{\infty} b_k^{\lfloor i/N \rfloor} s_k^{(i)} \psi(t - iT_c) + v(t). \quad (1)$$

A_k and $b_k = (\ldots, b_k^{(0)}, \; b_k^{(1)}, \; b_k^{(2)}, \ldots)$ denote, respectively, the signal amplitude and the data sequence of user k. Also, $\{s_k^{(i)}\}_{i=0}^{N-1}$ is the corresponding signature code sequence of ± 1's, with the length of the PN codes to be N, and $\psi(t)$ is a normalized chip waveform with chip duration T_c. Parameter $\beta_k(t)$ denotes the complex attenuation due to Rayleigh fading channel, and the additive background noise, $v(t)$, is assumed to be a white Gaussian (or AWGN); it has zero-mean and with variance σ^2. Before transmission, each data signal of user k is spread by N-chip signature sequence, $\{s_k^{(i)}\}_{i=0}^{N-1}$,in time domain. At the receiver, after chip-matched filtering and followed by the chip rate sampling, the output vector of the chip-matched filter can be represented as

$$\mathbf{r}(n) = \sum_{k=1}^{K} A_k\beta_k(n) b_k(n) \mathbf{s}_k + \mathbf{v}(n), \quad (2)$$

where $\mathbf{s}_t = [s_k^{(0)} \;\; s_k^{(1)} \;\; \ldots \;\; s_k^{(N-1)}]^T$ is the signature waveform vector and $\mathbf{v}(n)$ is the noise vector. For simplicity, we assume that the first user is the desired user, its nth transmitted data bit can be extracted from the output of the adaptive multiuser detector, i.e., $\hat{b}_1(n) = \text{sgn}(\text{Re}[e^{-j\hat{\phi}_1(n)} y(n)])$, where $\hat{\phi}_1(n)$ denotes the estimated phase of $\beta_1(n)$ for compensation and $y(n)$ is defined as

$$\begin{aligned} y(n) &= \mathbf{w}^H \mathbf{r}(n) \\ &= A_1\beta_1(n) b_1(n) \mathbf{w}^H \mathbf{s}_1 + \mathbf{u}^H(n)\tilde{\mathbf{b}}(n) + \mathbf{w}^H \mathbf{v}(n). \quad (3) \end{aligned}$$

It is noted that if the non-coherent modulation technique, e.g., DPSK [21], instead of BPSK is utilized, the nth information data bit can be extracted without the knowledge of phase information. Here, $\mathbf{w}$ is the $N\times 1$ weight vector of the adaptive multiuser detector for the DS-CDMA system. The first term on the right hand side of (3) contains the nth data bit related to the desired user. While the second and third terms relate to the effects of MAI and the background noise, in which vectors $\mathbf{u}(n) = [u_2(n) \;\; u_3(n) \;\; \ldots \;\; u_K(n)]^T$ with $u_k(n) = A_k\beta_k(n)\mathbf{w}^H\mathbf{s}_k$ and $\tilde{\mathbf{b}}(n) = [b_2(n) \;\; b_3(n) \;\; \ldots \;\; b_K(n)]^T$ correspond to the interferences of $K-1$ users. We can extract the desired symbol, $b_1(n)$, from (3), if $\mathbf{w}$ is chosen such that $\mathbf{w}^H\mathbf{s}_1$=1 and the effect of MAI can be suppressed, successfully.

3. Linearly Constrained Adaptive Constant Modulus RLS Algorithm

As described earlier, the LCCM algorithm could provide great performance improvement for the adaptive DS-CDMA multiuser detector; in terms of MAI suppression and its robustness against the code and timing mismatch problems. With the constant modulus (CM) approach, the output signal of the multiuser detector, $y(n)$, is assumed to be with constant envelope, e.g., $|y(n)|^2 = A_1^2 = \alpha$ (e.g., A_1 is the amplitude of desired signal) [6]–[14]. Since the constant envelope, α, is related directly to the desired user amplitude, A_1. Under the time-varying environments, from (3) the desired user amplitude is varied with time, e.g., $A_1\beta_1(n)$, and is not known exactly in the receiver end. Thus, the improper selection of α will result in serious performance degradation. To combat this problem, in this section, based on the configuration described in Fig. 1, we introduce a new scheme, referred to as the LC-ACM-RLS algorithm. It can be employed to adaptively implement the constrained optimal weight vector of the DS-CDMA detector, and to track the optimal value of α, simultaneously. This includes the case that $\alpha(i) = |A_1\beta_1(i)|^2$ is time varying, while in the conventional approach the value of α is a constant [6]–[14]. With the approach similar to [6]–[14], we may define the error signal, $e(i) = |y(i)|^2 - \alpha(i)$. To proceed with the derivation of the new LC-ACM-RLS algorithm, the cost function of the weighted least-squares (LS) error is defined as [11]

$$\begin{aligned} J_{\text{LS}}(\mathbf{w}(n), \alpha(n)) &= \sum_{i=1}^{n} \lambda^{n-i} |\alpha(i) - |y(i)|^2|^2 \\ &= \sum_{i=1}^{n} \lambda^{n-i} |\alpha(i) - y^*(i)\mathbf{w}^H(n)\mathbf{r}(i)|^2 \\ &= \sum_{i=1}^{n} \lambda^{n-i} |\alpha(i) - \mathbf{w}^H(n)\tilde{\mathbf{r}}(i)|^2. \quad (4) \end{aligned}$$

Where λ is the forgetting factor, and a new intermediate input data vector $\tilde{\mathbf{r}}(n) = y^*(n)\mathbf{r}(n)$ is introduced in (4). The weight vector is embedded in $\tilde{\mathbf{r}}(n)$, since $y^*(n) = \mathbf{r}^H(n)\mathbf{w}(n)$. For simplicity, the concept of iterative optimization ap-

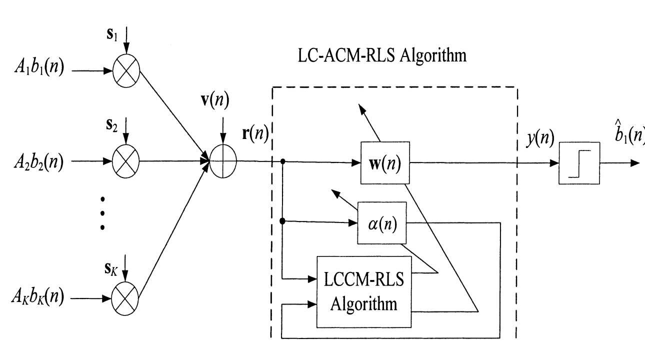


Fig. 1 The block diagram of the blind LC-ACM-RLS detector for DS-CDMA system.

proach addressed in [11], [15] can be employed, in which the weight vector $\mathbf{w}(n)$ is replaced by the priori weight vector, $\mathbf{w}(n-1)$. That is, $\tilde{\mathbf{r}}(n) \approx \mathbf{r}(n)\mathbf{r}^H(n)\mathbf{w}(n-1)$. Via the Lagrange multipliers approach, the constrained LS solution of weight vector, $\mathbf{w}(n)$, subjects to the desired-code constraint; $\mathbf{w}^H(n)\mathbf{s}_1 = 1$, can be obtained, i.e.,

$$\mathbf{w}(n) = \mathbf{R}^{-1}(n)\theta(n) + \mathbf{R}^{-1}(n)\mathbf{s}_1(\mathbf{s}_1^T\mathbf{R}^{-1}(n)\mathbf{s}_1)^{-1}(1-\mathbf{s}_1^T\mathbf{R}^{-1}(n)\theta(n)), \tag{5}$$

where the autocorrelation matrix, $\mathbf{R}(n)$, is defined as

$$\mathbf{R}(n) = \sum_{i=1}^{n}\lambda^{n-i}\tilde{\mathbf{r}}(i)\tilde{\mathbf{r}}^H(i) = \lambda\mathbf{R}(n-1) + \tilde{\mathbf{r}}(n)\tilde{\mathbf{r}}^H(n), \tag{6}$$

Also, the cross-correlation vector $\theta(n)$ is designated as

$$\theta(n) = \sum_{i=1}^{n}\lambda^{n-i}\alpha(i)\tilde{\mathbf{r}}(i) = \lambda\theta(n-1) + \alpha(n)\tilde{\mathbf{r}}(n). \tag{7}$$

It denotes the information including intermediate input data vector $\tilde{\mathbf{r}}(n)$ and the time-variant desired envelope $\alpha(n)$, which appears only in the cross-correlation vector, $\theta(n)$. While in the conventional LCCM approach the scalar variable, $\alpha(n)$, of (4) is fixed or time-invariant, and can be viewed as the desired signal in the conventional LS approach. Following the similar approach as suggested in [11], and after some mathematical manipulation, the LCCM-RLS algorithm, a recursive form of (5), can be derived

$$\mathbf{w}(n) = \mathbf{w}(n-1) + [\mathbf{I} - \mathbf{g}(n)\varphi^{-1}(n)\mathbf{s}_1^T]\mathbf{k}(n)e^*(n|n-1), \tag{8}$$

where $\mathbf{I}$ is the $N \times N$ identity matrix, and the predicted error signal is designated as

$$e(n|n-1) = \alpha(n) - \mathbf{w}^H(n-1)\tilde{\mathbf{r}}(n). \tag{9}$$

Since in the receiver, the constant envelope $\alpha(n)$ is not available, and has to be estimated, adaptively. We will discuss this later (in (16)). The corresponding parameters used to implement (8) are defined as follows:

$$\mathbf{k}(n) = \mathbf{R}^{-1}(n)\tilde{\mathbf{r}}(n) = \frac{\mathbf{R}^{-1}(n-1)\tilde{\mathbf{r}}(n)}{\lambda + \tilde{\mathbf{r}}^H(n)\mathbf{R}^{-1}(n-1)\tilde{\mathbf{r}}(n)}, \tag{10}$$

$$\mathbf{R}^{-1}(n) = \lambda^{-1}\mathbf{R}^{-1}(n-1) - \lambda^{-1}\mathbf{k}(n)\tilde{\mathbf{r}}^H(n)\mathbf{R}^{-1}(n-1), \tag{11}$$

$$\mathbf{g}(n) = \mathbf{R}^{-1}(n)\mathbf{s}_1 = \lambda^{-1}[\mathbf{I} - \mathbf{k}(n)\tilde{\mathbf{r}}^H(n)]\mathbf{g}(n-1), \tag{12}$$

and

$$\phi(n) = \mathbf{s}_1^T\mathbf{R}^{-1}(n)\mathbf{s}_1 = \lambda^{-1}[\phi(n-1) - \rho(n)\eta(n)]. \tag{13}$$

It is noted that the fundamental discussion of choosing the initial or starting value of $\mathbf{R}(0)$ for implementing the RLS algorithm was provided in [16]. To assure the non-singularity of $\mathbf{R}(n)$, we initialize the recursion of $\mathbf{R}^{-1}(n)$ by simply choosing a starting value $\mathbf{R}^{-1}(0) = \delta^{-1}\mathbf{I}$ [16]. In (13) the scalar parameters $\rho(n)$ and $\eta(n)$ are defined as $\rho(n) = \mathbf{s}_1^T\mathbf{k}(n)$ and $\eta(n) = \tilde{\mathbf{r}}^H(n)\mathbf{g}(n-1)$, respectively. By applying the inversion lemma to (13), it gives

$$\phi^{-1}(n) = \lambda[1 + q(n)\eta(n)]\phi^{-1}(n-1), \tag{14}$$

with

$$q(n) = \frac{\phi^{-1}(n-1)\rho(n)}{1 - \eta(n)\phi^{-1}(n-1)\rho(n)}. \tag{15}$$

In (9) or (7) the exact knowledge of $\alpha(n)$ is not available. To solve this problem, based on the weight vector $\mathbf{w}(n)$ obtained in (8), a gradient algorithm is derived to estimate $\alpha(n)$. To do so, we simply minimize the cost function defined in (4) with respect to $\alpha(n)$. With the gradient approach, the updating equation is given by

$$\alpha(n+1) = \alpha(n) + \frac{1}{2}\mu[-\nabla_\alpha J_{\mathrm{LS}}(\mathbf{w}(n), \alpha(n))], \tag{16}$$

where the step-size μ controls the stability and the convergence speed. The algorithm described in (16) is called the ACM algorithm, and associated with (8) we obtain the complete LC-ACM-RLS algorithm. To simplify (16), again, from (4), the partial derivative of cost function, with respect to $\alpha(n)$, i.e., $\nabla_\alpha J_{\mathrm{LS}}(\mathbf{w}(n), \alpha(n))$, is defined as

$$\begin{aligned}
\nabla_\alpha J_{\mathrm{LS}}(\mathbf{w}(n), \alpha(n)) &= \frac{\partial J_{\mathrm{LS}}(\mathbf{w}(n), \alpha(n))}{\partial\alpha(n)} \\
&= 2\alpha(n) - [\mathbf{w}^H(n)\tilde{\mathbf{r}}(n) + \frac{\partial\mathbf{w}^H(n)}{\partial\alpha(n)}\alpha(n)\tilde{\mathbf{r}}(n)] - \\
&\quad [\tilde{\mathbf{r}}^H(n)\mathbf{w}(n) + \alpha(n)\tilde{\mathbf{r}}^H(n)\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)}] + \\
&\quad [\frac{\partial\mathbf{w}^H(n)}{\partial\alpha(n)}\tilde{\mathbf{r}}(n)\tilde{\mathbf{r}}^H(n)\mathbf{w}(n) + \mathbf{w}^H(n)\tilde{\mathbf{r}}(n)\tilde{\mathbf{r}}^H(n)\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)}] \\
&= 2\alpha(n) - 2\mathbf{w}^H(n)\tilde{\mathbf{r}}(n) \\
&\quad + 2[\mathbf{w}^H(n)\tilde{\mathbf{r}}(n)\tilde{\mathbf{r}}^H(n) - \alpha(n)\tilde{\mathbf{r}}^H(n)]\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)} \\
&= 2[\alpha(n) - \tilde{y}(n)][1 - \tilde{\mathbf{r}}^H(n)\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)}],
\end{aligned} \tag{17}$$

where $\tilde{y}(n) = \mathbf{w}^H(n)\tilde{\mathbf{r}}(n)$. According to (5) and using the definition of (7), the gradient vector, $\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)}$, of (17) can be easily derived, i.e.,

$$\begin{aligned}
\frac{\partial\mathbf{w}(n)}{\partial\alpha(n)} &= [\mathbf{I} - \mathbf{R}^{-1}(n)\mathbf{s}_1(\mathbf{s}_1^T\mathbf{R}^{-1}(n)\mathbf{s}_1)^{-1}\mathbf{s}_1^T]\mathbf{R}^{-1}(n)\tilde{\mathbf{r}}(n) \\
&= \mathbf{k}(n) - \varphi^{-1}(n)\rho(n)\mathbf{g}(n).
\end{aligned} \tag{18}$$

Finally, the complete LC-ACM-RLS algorithm can be performed with (8), (9) and (16), and the associated parameters involved in (8) and (16).

4. Optimal MMSE Solution of the LCCM Receiver

In the previous section, we proposed a new LC-ACM-RLS algorithm to adaptively update the constrained LS weight vector for LCCM receiver, and to track the constant envelope, $\alpha(n)$, simultaneously. To verify the advantage of the new proposed LC-ACM-RLS algorithm, it is of interest to compare with the optimal MMSE solution of the LCCM receiver. It is noted that, for simplicity, the optimal MMSE solution for the LCCM is derived and analyzed, under the AWGN (additive white Gaussian) channel. It can be viewed as an upper bound of the proposed LC-ACM-RLS algorithm. Ideally, the LC-ACM-RLS algorithm would converge to the MMSE solution of the LCCM receiver. Particularly, it is significant to examine how good the proposed LC-ACM-RLS algorithm could approach to the MMSE solution [16]. Thus, in what follows, we will concentrate on the analytic determination, with the MMSE approach, for the optimal value of α under the AWGN channel. That is, the effect of the fading parameter, $\beta_k(n)$, of (2) is ignored. For the purpose of comparison, the corresponding output signal-to-interference-plus-noise ratio (SINR) will be evaluated.

4.1 Optimal α of the LCCM Receiver for Arbitrary Weight Vector

For simplicity, let us consider the LCCM receiver of synchronous DS-CDMA system. The constrained weight vector, $\mathbf{w}$, is determined according to the constrained MMSE cost function:

$$\xi(\mathbf{w},\alpha) = E\{|\alpha - y^2(n)|^2\}, \text{ subject to } \mathbf{w}^T\mathbf{s}_1 = 1. \qquad (19)$$

For further discussion, we expand $E\{|\alpha - y^2(n)|^2\}$ as

$$E\{|\alpha - y^2(n)|^2\} = \alpha^2 - 2\alpha E\{y^2(n)\} + E\{y^4(n)\}. \qquad (20)$$

Without loss of generality, we assume that α is unknown in the receiver. Next, with the linear constraint, $\mathbf{w}^T\mathbf{s}_1 = 1$, the output signal of the LCCM receiver can be expressed as

$$y(n) = \mathbf{w}^T\mathbf{r}(n) = A_1 b_1(n) + \mathbf{u}^T\tilde{\mathbf{b}}(n) + \mathbf{w}^T\mathbf{v}(n), \qquad (21)$$

where vectors $\tilde{\mathbf{b}}(n)$ and $\mathbf{u}$ were defined in (3) of Sect. 2, which are related to the information bits and amplitudes of $K-1$ interfering users, respectively. Since in this section the AWGN channel is considered, the term of complex attenuation, $\beta_k(n)$, defined in (3), is ignored and did not appear in (21). Substituting (21) into (20), (19) reduces to

$$\xi(\mathbf{w},\alpha) = \alpha^2 - 2\alpha\mathbf{w}^T\mathbf{R}\mathbf{w} + 3(\mathbf{w}^T\mathbf{R}\mathbf{w})^2 - 2\sum_{k=2}^{K} u_k^4 - 2A_1^4 \qquad (22)$$

with

$$E\{y^2(n)\} = A_1^2 + \mathbf{u}^T\mathbf{u} + \sigma^2\mathbf{w}^T\mathbf{w} = \mathbf{w}^T\mathbf{R}\mathbf{w} \qquad (23)$$

and

$$\begin{aligned} E\{y^4(n)\} &= E\{A_1^4 b_1^4(n) + (\mathbf{u}^T\tilde{\mathbf{b}}(n))^4 + (\mathbf{w}^T\mathbf{v}(n))^4 \\ &\quad + 6A_1^2 b_1^2(n)(\mathbf{u}^T\tilde{\mathbf{b}}(n))^2 \\ &\quad + 6A_1^2 b_1^2(n)(\mathbf{w}^T\mathbf{v}(n))^2 \\ &\quad + 6(\mathbf{w}^T\mathbf{v}(n))^2(\mathbf{u}^T\tilde{\mathbf{b}}(n))^2\} \\ &= A_1^4 + 3(\mathbf{u}^T\mathbf{u})^2 - 2\sum_{k=2}^{K} u_k^4 + 3\sigma^4(\mathbf{w}^T\mathbf{w})^2 \\ &\quad + 6A_1^2\mathbf{u}^T\mathbf{u} + 6A_1^2\sigma^2\mathbf{w}^T\mathbf{w} + 6\sigma^2\mathbf{w}^T\mathbf{w}\mathbf{u}^T\mathbf{u} \\ &= 3(\mathbf{w}^T\mathbf{R}\mathbf{w})^2 - 2\sum_{k=2}^{K} u_k^4 - 2A_1^4. \end{aligned} \qquad (24)$$

In (22), the statistical auto-correlation matrix is designated by $\mathbf{R} = E\{\mathbf{r}(n)\mathbf{r}^T(n)\} = \sum_{k=1}^{K} A_k^2\mathbf{s}_k\mathbf{s}_k^T + \sigma^2\mathbf{I}_N$, in which $\mathbf{I}_N$ is the $N{\times}N$ identity matrix. Since $b_k(n)$ is independent equiprobable discrete random variable of ± 1's, we have $E\{b_k(n)\} = E\{b_k^3(n)\} = 0$ and $E\{b_k^2(n)\} = E\{b_k^4(n)\} = 1$. Also, the additive white Gaussian noise $v(n)$ is assumed to be statistically independent to data sequences, $b_k(n)$. We note that in (19) the constrained MMSE cost function is function of $\mathbf{w}$ and α. First, we would like to determine the optimal value of α, based on the LCCM receiver, for arbitrary weight vector $\mathbf{w}$. To obtain the optimal value of α, we may simply take the first derivative of (19), with respect to α, and set it to null, i.e.,

$$\frac{\partial\xi(\mathbf{w},\alpha)}{\partial\alpha} = 2\alpha - 2\mathbf{w}^T\mathbf{R}\mathbf{w} = 0. \qquad (25)$$

From (25) we obtain the optimal value of constant envelope $\alpha = \mathbf{w}^T\mathbf{R}\mathbf{w}$ for arbitrary weight vector.

4.2 Optimal Weight Vector and Output SINR of the LCCM Receiver with Optimal α

In this section, the optimal weight vector of the constrained cost function, described in (19), can be solved directly via the Lagrange multiplier approach. For convenience, the constrained cost function with single constraint, $\mathbf{w}^T\mathbf{s}_1 = 1$, can be rewritten as

$$J(\mathbf{w}) = \xi(\mathbf{w}) - 8\gamma(\mathbf{w}^T\mathbf{s}_1 - 1), \qquad (26)$$

where parameter 8γ is called the Lagrange multiplier, and scalar 8 is adopted to make the solution in a compact form. To obtain the constrained optimal weight vector $\mathbf{w}$, we simply take the first partial derivative with respect to $\mathbf{w}$ by using $\alpha = \mathbf{w}^T\mathbf{R}\mathbf{w}$ and set it to be null vector, i.e.,

$$\begin{aligned} \frac{\partial J(\mathbf{w})}{\partial\mathbf{w}} &= \frac{\partial\xi(\mathbf{w})}{\partial\mathbf{w}} - 8\gamma\mathbf{s}_1 \\ &= 8\mathbf{R}\mathbf{w}\mathbf{w}^T\mathbf{R}\mathbf{w} - 8\sum_{k=2}^{K}\mathbf{s}_k u_k^3 - 8A_1^4\mathbf{s}_1 - 8\gamma\mathbf{s}_1 = \mathbf{0}. \end{aligned} \qquad (27)$$

With the constraint, $\mathbf{w}^T\mathbf{s}_1 = 1$, and from (27), γ can be solved, it gives

$$\begin{aligned} \gamma &= (\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}\mathbf{w}^T\mathbf{R}\mathbf{w} \\ &\quad - (\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}\mathbf{s}_1^T\mathbf{R}^{-1}\sum_{k=2}^{K}\mathbf{s}_k u_k^3 - A_1^4. \end{aligned} \qquad (28)$$

After substituting (28) into (27), we have

$$\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}} = 8\mathbf{R}\mathbf{w}\mathbf{w}^T\mathbf{R}\mathbf{w} - 8\mathbf{s}_1(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}\mathbf{w}^T\mathbf{R}\mathbf{w} - 8\sum_{k=2}^{K}\mathbf{s}_k u_k^3 - 8(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}\mathbf{s}_1^T\mathbf{R}^{-1}\sum_{k=2}^{K}\mathbf{s}_k u_k^3 = \mathbf{0}. \tag{29}$$

We note that in [7]–[10], it has been proved that the LCCM approach has the capability of removing the effect of MAI, completely. Since for synchronous DS-CDMA system, ideally, we have $\mathbf{w}^T\mathbf{s}_1 = 1$ and $\mathbf{w}^T\mathbf{s}_k \ll 1$, for $k \neq 1$. In (29) the terms with u_k^3 (e.g. $u_k = A_k\mathbf{w}^T\mathbf{s}_k$) can be ignored compared with other terms of (29). Thus (29) reduces to

$$\mathbf{R}\mathbf{w}\mathbf{w}^T\mathbf{R}\mathbf{w} - \mathbf{s}_1(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}\mathbf{w}^T\mathbf{R}\mathbf{w} \approx \mathbf{0}. \tag{30}$$

Or

$$\mathbf{w}_{\text{opt}} \approx \mathbf{R}^{-1}\mathbf{s}_1(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}, \tag{31}$$

if and only if $\mathbf{w}^T\mathbf{R}\mathbf{w} > 0$. Under the AWGN channel environment, by definition of $\mathbf{R}$ (see two lines below Eq. (24)), the term of $\sigma^2\mathbf{I}_N$ will lead to ensure that $\mathbf{R}$ is a nonsingular matrix, where σ^2 is the variance of channel noise, so that $\mathbf{R}^{-1}$ exits. Under the linear constraint, $\mathbf{w}^T\mathbf{s}_1 = 1$, we recalled that in (23) the average output power was defined as: $\mathbf{w}^T\mathbf{R}\mathbf{w} = A_1^2 + \mathbf{u}^T\mathbf{u} + \sigma^2\mathbf{w}^T\mathbf{w}$, in which $\mathbf{u}^T\mathbf{u}$ and $\sigma^2\mathbf{w}^T\mathbf{w}$ are greater or equal to zero, thus, it implies that $\mathbf{w}^T\mathbf{R}\mathbf{w} > 0$ (since usually the desired user's amplitude could not be null). Furthermore, with the optimal weight vector defined in (31), the optimal value of α, based on the LCCM receiver, can be expressed as $\alpha_{\text{opt}} = \mathbf{w}_{\text{opt}}^T\mathbf{R}\mathbf{w}_{\text{opt}} \approx (\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}$. Consequently, the corresponding output SINR for LCCM receiver is given by

$$\text{SINR} \approx \frac{A_1^2\mathbf{w}_{\text{opt}}^T\mathbf{s}_1\mathbf{s}_1^T\mathbf{w}_{\text{opt}}}{\mathbf{w}_{\text{opt}}^T\mathbf{R}\mathbf{w}_{\text{opt}} - A_1^2\mathbf{w}_{\text{opt}}^T\mathbf{s}_1\mathbf{s}_1^T\mathbf{w}_{\text{opt}}} = \frac{A_1^2}{(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1} - A_1^2}. \tag{32}$$

The results described in (31) and (32) are, indeed, equivalent to the optimal solution of the LCMV criterion [4].

5. Computer Simulation Results

In this section, computer simulations are carried out to document the merits of the newly proposed LC-ACM-RLS algorithm for blind multiuser detector of DS-CDMA systems. Here the downlink channel with the BPSK modulation technique is considered. Since in the practical applications, generally, in the uplink channel the power control is used to assure that each mobile within the base station coverage area provides the same signal level to the base station receiver. Also, an effective power control could be used to compensate for the slowly fading and minimizes the effect of fast fading [19], [20]. Therefore, the effect of time-variant fading in the downlink channel is more significant and is emphasized in this paper. To generate the signature code sequence for 10 users including the desired user, Gold code with length N=31 is employed. For investigating the capability of MAI suppression, the power of the desired user is assumed to be 20 dB weaker than all other 9 users (e.g., the near-far problem). As a convention, the initial value of autocorrelation matrix with LS approach is chosen to be $\mathbf{R}^{-1}(0) = \delta^{-1}\mathbf{I}$, where $\delta < 0.01\sigma_r^2$ and σ_r^2 can be estimated from the average power of the received signal [18].

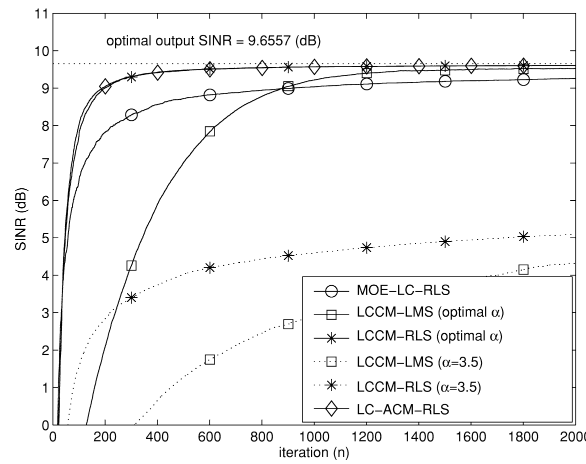


Fig. 2 Learning curves comparison of output SINR for different algorithms.

First, let us consider the case of time-invariant (constant) envelope in the AWGN channel. The forgetting factor is chosen to be λ=1 for the proposed LC-ACM-RLS algorithm and other RLS-based algorithms. Also, the step-size used in (16) for the gradient algorithm is chosen to be μ=0.1, for tracking the scalar variable, $\alpha(n)$. For fair comparison, the results in terms of SINR are given in Fig. 2; they are the average of 100 independent runs. From Fig. 2, we found that the new proposed LC-ACM-RLS algorithm has the same performance as that using the LCCM-RLS algorithm with $\alpha_{\text{opt}} = (\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}$. They have a faster convergence property and a largest steady state output SINR value than the MOE-LC-RLS algorithm, and the LCCM-RLS algorithm with different value of α, viz., α=3.5 (incorrect-value) [6]–[10] and the LCCM-LMS algorithm. Moreover, the LCCM-RLS algorithms have faster convergence rate than LCCM-LMS algorithms (implementing with applicable values of step size) with the same value of α. With the theoretical optimal LCCM solution, the values of output SINR for different values of A_1 for SNR=5 dB, 10 dB and 15 dB, are listed in Table 1, as reference. In all cases, we found that the steady state output SINR values of the proposed LC-ACM-RLS algorithm agreed quite well with the theoretical values.

Next, we consider the case of time-varying environments, such as hand-off and fading channel and the forgetting factor λ=0.998 is employed. Under such circumstance the amplitude of desired user is varied with time, the conventional LCCM algorithms might diverge. For investigation, first we consider the case that hand-off occurs between two base stations, e.g., BS_1 and BS_2. For convenience, we also assume that, initially, the desired user is in

Table 1 Comparison of output SINR performance between proposed LC-ACM-RLS algorithm and theoretical value, which has been derived based on MMSE approach in (32), with different amplitude of desired user, for SNR=5, 10, and 15 dB.

SNR	A_1=0.1	A_1=1	A_1=5
5 dB (SINR_{opt}=4.6569 dB)	4.5106 (dB)	4.5127 (dB)	4.5091 (dB)
10 dB (SINR_{opt}=9.6557 dB)	9.5542 (dB)	9.5571 (dB)	9.5519 (dB)
15 dB (SINR_{opt}=14.6554 dB)	14.574 (dB)	14.5702 (dB)	14.5698 (dB)

BS_1 with totally 10 users and A_1=4 (the amplitude of desired user). Following that we assume that at 2000th iteration the hand-off is taken place, and only 5 users are in BS_2 with A_1=2. Ideally, in this case, the corresponding optimal values of $\alpha(n)$ before and after hand-off are chosen to be α_{opt}=17.732 (for $A_1^2 = 16$) and α_{opt}=4.4223 (for $A_1^2 = 4$), respectively, for SNR=10 dB. As shown in Fig. 3, when the desired user is in BS_1 the conventional LCCM-RLS algorithm, with α_{opt}=17.732, outperforms the MOE-LC-RLS algorithm. But, it degrades after hand-off (the constant envelope, α_{opt}=17.732, is still employed in BS_2) being taken. That is incorrect because in BS_2 with A_1=2, the corresponding optimal value of constant envelope should be α_{opt}= 4.4223. But, this information is not available at the receiver end. However, this is not the case when our new proposed LC-ACM-RLS algorithm is employed. It can be used to track and update $\alpha(n)$, adaptively, to achieve the desired SINR performance (see Fig. 3). The tracking capability of $\alpha(n)$ with the proposed LC-ACM-RLS algorithm is illustrated in Fig. 4, with the same parameters of Fig. 3. As evident from Fig. 4, our proposed scheme has the superior tracking capability.

For further investigation, a more practical case, the Rayleigh fading channel environment is considered. Here, the channel is generated with Jake's model in terms of normalized Doppler frequency $f_d T_b$=0.0025, where parameter f_d is the maximum Doppler frequency and T_b is the symbol period. In this case, first the non-coherent receiver with the DPSK modulation technique [21] is adopted, where the amplitude A_1=1 is selected. It does not require the knowledge of phase information. Due to the fading parameter, $\beta_1(n)$, the value of envelope, $\alpha(n) = |A_1\beta_1(n)|^2$, will be time varying. For simulation, the envelope is generated from the random variable with the Rayleigh distribution described in Fig. 6(a). For performance comparison, the BER versus SNR is illustrated in Fig. 5(a). The BER is plotted with 10000 symbols and are the average of 500 independent runs. From Fig. 5(a), we observed that the proposed LC-ACM-RLS algorithm has the best BER performance. It performs very close to the least square errors (LSE-LC-RLS) approach with reference signal transmitted from the

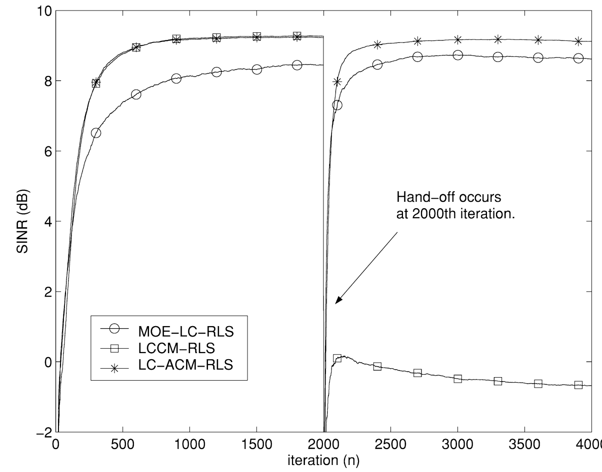


Fig. 3 Comparison of output SINR performance and tracking capability for different algorithms, where amplitude of user 1 changes due to hand-off occurs at 2000th iteration, with 10 users and A_1=4 in BS_1 and 5 users and A_1=2 in BS_2, for SNR=10 dB.

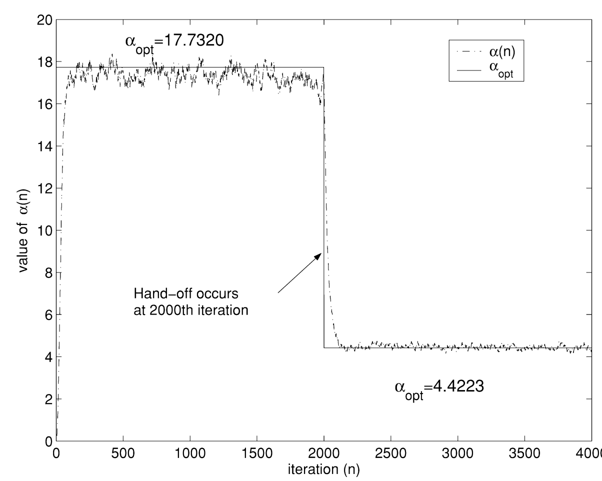
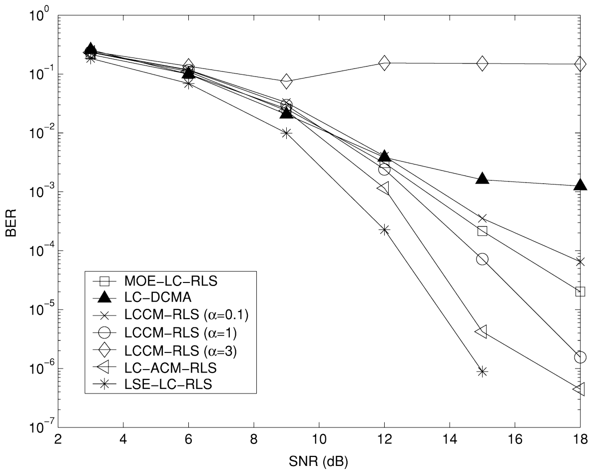


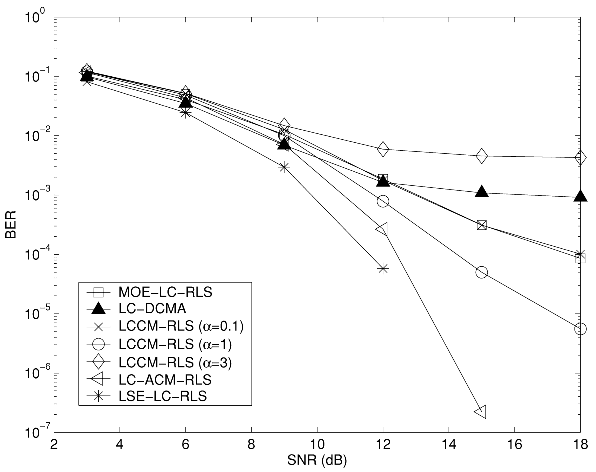
Fig. 4 Tracking capability comparison of the LC-ACM-RLS algorithm for the time-varying envelope, $\alpha(n)$, as demonstrated in Fig. 3. Where hand-off is taken place at 2000th iteration, with 10 users and A_1=4 in BS_1 and 5 users and A_1=2 in BS_2, for SNR=10 dB.

transmitter. It outperforms the one with the MOE-LC-RLS algorithm, the LC-DCMA algorithm and the conventional LCCM-RLS algorithm with different value of α (α = 0.1, 1, and 3, respectively). For comparison, the results with the BPSK coherent receiver and having the perfect phase estimation of channel coefficients are given in Fig. 5(b). Better BER performance can be achieved compared with that given in Fig. 5(a), with non-coherent receiver. The implication of these results is that with fixed values of α the LCCM approach is very sensitive to the amplitude variation due to Rayleigh fading channel. Also, as observed from Fig. 6(b), the LC-ACM-RLS algorithm can be used to track the time-varying envelope (due to channel characteristic) very well.

In fact, the proposed algorithm can be extended to the multipath-fading channel; the formulation is derived in Appendix. For investigating the capability of MAI suppres-



(a)



(b)

Fig. 5 Performance comparison of BER for different algorithms under Rayleigh fading channel environment with (a) DPSK and (b) BPSK, with perfect phase estimation, modulation techniques.

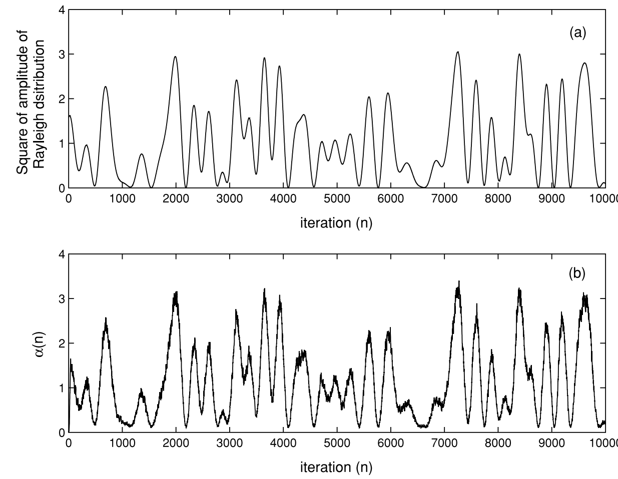


Fig. 6 Tracking capability of the time-varying envelope, $\alpha(n)$, for Rayleigh fading channel: (a) The distribution of Rayleigh fading envelope, (b) Tracking curve of $\alpha(n)$ with respect to Rayleigh fading channel.

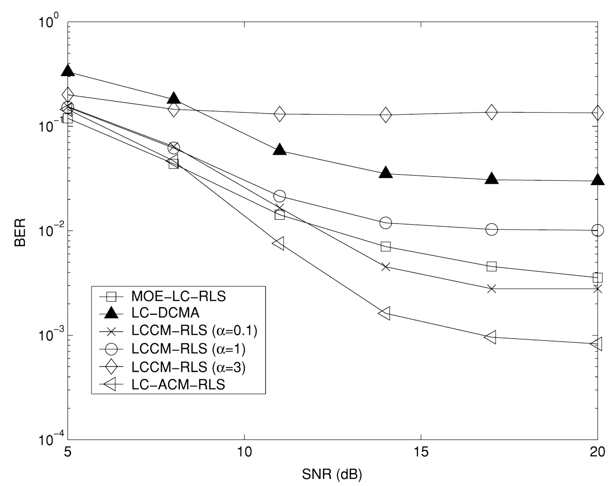


Fig. 7 Performance comparison of BER for different algorithms under time-varying multipath fading channel environment with DPSK modulation technique.

sion under the effect of near-far problem, we assume that the powers of 4 interfered users are 10 dB over the desired user, and 5 users are with 5 dB higher than the desired user. Moreover, the number of paths is set to be 3 with relative power given by 0, −3, and −6 dB. To verify the improvement over the conventional LCCM receivers, the time-varying channel environment is considered, in which the amplitude $\tilde{A}_1(n)$ is varied with time. Also, the gain of each path is generated with Jake's model with normalized Doppler frequency $f_d T_b$=0.0025. In this case, the amplitude A_1=1 is adopted and under the multipath fading channel environment, α will be time-varying and behaved very similar to Fig. 6. As before, the proposed LC-ACM-RLS algorithm and the LC-DCMA algorithm [17] with the DPSK modulation could be employed to avoid the phase ambiguity in the blind channel estimation. On the other hand, with the conventional LCCM-RLS algorithm, with different α (α=0.1, 1, and 3, respectively), the PASTd algorithm [23] is employed to evaluate the eigenvector of the corresponding minimum eigenvalue of matrix $\mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1$ for channel parameter estimation. The performance comparison of BER versus SNR is illustrated in Fig. 7. Again, the proposed LC-ACM-RLS algorithm has superior BER performance over the MOE-LC-RLS algorithm and the conventional LCCM-RLS algorithm with different value of α. Again, we learn that with fixed values of α, the LCCM approach is more sensitive to the amplitude variation due to time-varying channels.

6. Conclusions

In this paper, we have proposed a novel LC-ACM-RLS algorithm to adaptively implement the optimal solution of the LCCM receiver for MAI suppression and to track the desired user amplitude (it is usually not available in the receiver), simultaneously. For the purpose of comparison, based on the MMSE approach in Sect. 4, we derived the theoretical value of optimal envelope of α, i.e., α_{opt} =

$(\mathbf{s}_1^T\mathbf{R}^{-1}\mathbf{s}_1)^{-1}$, for constrained optimal weight vector of the LCCM receiver. In general, with unknown value of α, our newly proposed LC-ACM-RLS algorithm could be employed to achieve better performance; in terms of output SINR and the BER, when compared with the conventional approaches. Also, better tracking capability of envelope for time-varying environment was observed.

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Appendix

In this appendix, the formulation of the proposed LC-ACM-RLS algorithm is derived and extended to the multipath fading channel environment. First, we would like to introduce the system model for the DS-CDMA receiver for the multipath fading channel.

A.1 System Model in Multipath Channel

To formulate the system model, let us consider a downlink DS-CDMA system with K users over multipath fading channels. We assume that the receiver is synchronized with the main path, thus the received signal is given by

$$r(t) = \sum_{k=1}^{K}\sum_{l=1}^{L} A_k\beta_l(t)\sum_{i=-\infty}^{\infty} b_k^{\lfloor i/N\rfloor} s_k(t - iT_c - \tau_l) + v(t). \tag{A·1}$$

with parameters defined in Sect. 2 and L denotes the number of paths. At the receiver, after chip-matched filtering and chip rate sampling, the equivalent base-band received signal vector $\mathbf{r}(n)$ is given by

$$\mathbf{r}(n) = \sum_{k=1}^{K} A_k \sum_{l=1}^{L} b_k(n)\beta_l(n)\mathbf{s}_{k,l} + \mathbf{ISI} + \mathbf{v}(n). \tag{A·2}$$

where **ISI** refers to the ISI element and $\mathbf{v}(n)$ is the noise vector. Here, $\mathbf{r}(n)$ and $\mathbf{v}(n)$ are designated as

$$\mathbf{r}(n) = [r_0(n), \ldots, r_{N-1}(n), r_0(n+1), \ldots, r_{d_L-1}(n+1)]^T \tag{A·3}$$

and

$$\mathbf{v}(n) = [v_0(n), \ldots, v_{N-1}(n), v_0(n+1), \ldots, v_{d_L-1}(n+1)]^T, \tag{A·4}$$

respectively. In (A·2) the signature vector of user k is denoted as

$$\mathbf{s}_{k,l} = [\underbrace{0, 0, \ldots, 0}_{d_l}, s_1^{(k)}, s_2^{(k)}, \ldots, s_N^{(k)}, \underbrace{0, 0, \ldots, 0}_{d_L - d_l}]. \quad (A\cdot 5)$$

In which parameter d_l is the delay related to lth path during the chip period, it is evaluated by $d_l = \lfloor \tau_l / T_c \rfloor$. Without loss of generality, we assume that it satisfies the following condition, $0 \leq d_l < N$ and d_L is the maximum value of delay. Furthermore, the received signal vector of (A·2) can be represented in a matrix form, i.e.,

$$\mathbf{r}(n) = \sum_{k=1}^{K} A_k b_k(n) \mathbf{C}_k \mathbf{h}(n) + \mathbf{ISI} + \mathbf{v}(n), \quad (A\cdot 6)$$

where $\mathbf{C}_k = [\mathbf{s}_{k,1}, \mathbf{s}_{k,2}, \ldots, \mathbf{s}_{k,L}]^T$ and $\mathbf{h}(n) = [\beta_1(n), \beta_2(n), \ldots, \beta_L(n)]^T$ is the unknown channel parameter vector. Also, we may rewrite (A·6) as

$$\mathbf{r}(n) = \sum_{k=1}^{K} \tilde{A}_k(n) b_k(n) \mathbf{C}_k \tilde{\mathbf{h}}(n) + \mathbf{ISI} + \mathbf{v}(n), \quad (A\cdot 7)$$

In (A·7), parameter $\tilde{A}_k(n)$ is defined as $\tilde{A}_k(n) = A_k \| \mathbf{h}(n) \|$, and $\tilde{\mathbf{h}}(n) = \frac{\mathbf{h}(n)}{\|\mathbf{h}(n)\|}$ is denoted as a normalized vector of $\mathbf{h}(n)$ with unit norm. We note that in the conventional LCCM approach $\| \mathbf{h}(n) \| = 1$ is adopted [22]; in (A·7) we decompose the effect of channel vector into $\tilde{A}_k(n)$ and $\tilde{\mathbf{h}}(n)$, which is not with unit norm any more. In [22], the LCCM-RLS algorithm was proposed and applied to the DS-CDMA receiver for multipath channels. It assumed that the channel vector is with unit norm constraint, e.g., $\| \mathbf{h}(n) \| = 1$, and was generated in the system model for simulation. It thus provided better capability for MAI and ISI suppression than the MOE-LC-RLS algorithm, and achieved better performance improvement.

A.2 The Optimal Weight Solution and Its Adaptive Implementation

Based on the system model described in Sect. A1, the linear constraint employed in Sect. 3, i.e., $\mathbf{w}^H(n)\mathbf{s}_1 = 1$, has to be changed by $\mathbf{C}_1^T \mathbf{w}(n) = \tilde{\mathbf{h}}(n)$ (or denotes $\mathbf{w}^H(n)\mathbf{C}_1 = \tilde{\mathbf{h}}^H(n)$). In consequence, the constrained LS solution of weight vector, $\mathbf{w}(n)$, can be derived as

$$\begin{aligned}\mathbf{w}(n) &= \mathbf{R}^{-1}(n)\theta(n) \\ &+ \mathbf{R}^{-1}(n)\mathbf{C}_1(\mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1)^{-1}(\tilde{\mathbf{h}}(n) - \mathbf{C}_1^T \mathbf{R}^{-1}(n)\theta(n))\end{aligned} \quad (A\cdot 8)$$

where $\mathbf{R}(n)$ and $\theta(n)$ where defined in (6) and (7), with $\tilde{\mathbf{r}}(n) = \mathbf{r}(n)\mathbf{r}^H(n)\mathbf{w}(n-1)$ and $\mathbf{r}(n)$ was defined in (A·7). However, in practical applications the channel parameters $\beta_l(n)$ are unknown and channel estimation is required. Here, referring to [22], we adopt the blind channel estimation procedure by minimizing $\hat{\mathbf{h}}^H(n)\mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1 \hat{\mathbf{h}}(n)$, subject to $\| \hat{\mathbf{h}}(n) \| = 1$. Hence, the solution is the eigenvector corresponding to the minimum eigenvalue of $\mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1$ (or the maximum eigenvalue of $(\mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1)^{-1}$). After performing certain mathematical manipulations, with the definitions of (10) and (11), the recursive form of (A·8) is derived as

$$\begin{aligned}\mathbf{w}(n) =& \mathbf{w}(n-1) + [\mathbf{I} - \mathbf{P}(n)\mathbf{\Gamma}^{-1}(n)\mathbf{C}_1^T]\mathbf{k}(n)e^*(n|n-1) \\ &+ \mathbf{P}(n)\mathbf{\Gamma}^{-1}(n)(\hat{\mathbf{h}}(n) - \hat{\mathbf{h}}(n-1)),\end{aligned} \quad (A\cdot 9)$$

and the vector $\tilde{\mathbf{h}}(n)$ in constraint is replaced by the estimated vector $\hat{\mathbf{h}}(n)$. In (A·9), parameters are defined as

$$\mathbf{P}(n) = \mathbf{R}^{-1}(n)\mathbf{C}_1 = \lambda^{-1}[\mathbf{I} - \mathbf{k}(n)\tilde{\mathbf{r}}^H(n)]\mathbf{P}(n-1) \quad (A\cdot 10)$$

$$\mathbf{\Gamma}(n) = \mathbf{C}_1^T \mathbf{R}^{-1}(n)\mathbf{C}_1 = \lambda^{-1}[\mathbf{\Gamma}(n-1) - \rho(n)\eta^H(n)] \quad (A\cdot 11)$$

Also, in (A·11) the vector parameters $\rho(n)$ and $\eta(n)$ are defined as $\rho(n) = \mathbf{C}_1^T \mathbf{k}(n)$ and $\eta(n) = \mathbf{P}^H(n-1)\tilde{\mathbf{r}}(n)$, respectively. In consequence, by applying the inversion lemma to (A·11), we obtain

$$\mathbf{\Gamma}^{-1}(n) = \lambda[\mathbf{I} + \mathbf{q}(n)\eta^H(n)]\mathbf{\Gamma}^{-1}(n-1) \quad (A\cdot 12)$$

with

$$\mathbf{q}(n) = \frac{\mathbf{\Gamma}^{-1}(n-1)\rho(n)}{1 - \eta^H(n)\mathbf{\Gamma}^{-1}(n-1)\rho(n)}. \quad (A\cdot 13)$$

To obtain the complete LC-ACM-RLS algorithm, we need to solve $\alpha(n)$ derived in (16) and (17). Based on the model of the multipath channel, the gradient vector of (17) has to be modified as

$$\frac{\partial \mathbf{w}(n)}{\partial \alpha(n)} = \mathbf{k}(n) - \mathbf{P}(n)\mathbf{\Gamma}^{-1}(n)\rho(n) \quad (A\cdot 14)$$

with the parameters defined in (A·10) to (A·13).

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