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Adaptive MC-CDMA receiver with constrained constant modulus IQRD-RLS algorithm for MAI suppression☆

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Abstract

The multicarrier code division multiple access (MC-CDMA) technique is considered to be one of the attractive candidates to achieve high data-rate for future wireless communication systems. In this paper, based on linearly constrained constant modulus (LCCM) least square (LS) criterion, a new robust adaptive constrained filtering algorithm, referred to as the LCCM inverse QRD-RLS (IQRD-RLS) algorithm, is devised for MC-CDMA detector. The proposed robust LCCM IQRD-RLS algorithm can be used to estimate the weights of the combining process to combat the multiple access interference (MAI), effectively, and is more robust to against the imperfect channel estimation error. By this approach we require only the knowledge of code sequences of desired user rather than the code sequences of other users. The superiority of the proposed algorithm for estimating the weights in the combining process is verified by evaluating the performance, in terms of output signal to interference and noise ratio (SINR) and bit error rate (BER). From computer simulation results we showed that it outperformed the conventional techniques, such as the maximum ratio combining (MRC), blind adaptation algorithm, least mean square algorithm with partitioned linear interference canceller structure (PLIC-LMS) and LCCM-gradient based approaches.

Keywords: Multicarrier; Linearly constrained constant modulus; Inverse QRD-RLS algorithm; Mirror effect; Mismatch problem

1. Introduction

In wireless communication systems due to their operation as multiple access systems, the significant structure interference is inherent in wireless channels, and is referred to as the multiple access interference (MAI) [17]. Also, to alleviate the near-far problem in currently implemented direct-sequence code division multiple access (DS-CDMA) mobile telephony systems, the technique of power control is employed. It has the advantage of lowering the transmitted power for each user and thereby extends battery life. In recent years, many adaptive processing techniques have been intensively used for such interference suppression [9,11,19–21]. Those interference suppression techniques can potentially alleviate the near-far problem in DS-CDMA; their use can loose the requirements on power control.

The multicarrier (MC) communication is commonly used to combat channel distortion and improve the spectral efficiency. The MC-CDMA is the combination of the orthogonal frequency division

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Nomenclature

$a^{(k)}$	signature sequence of the kth user
$b^{(k)}$	data sequence of the kth user
$c_m^{(k)}$	code signal across the mth carrier branch of the kth user
$\mathbf{C}$	constraints matrix
$\mathbf{e}(n)$	error vector
$e(n, n-1)$	priori estimation error
$e_{\mathrm{unc}}(n, n-1)$	unconstrained priori estimation error
$\mathbf{f}$	desired response vector
$\mathbf{F}(n)$	projection operator
$\mathbf{i}$	MAI vector
$\mathbf{k}(n)$	adaptation or Kalman gain defined by $\mathbf{k}(n) = \mathbf{g}(n)/t(n)$
$\mathbf{n}$	background noise vector
$\mathbf{P}(n)$	orthogonal matrix which is product by N Givens rotation
$\mathbf{Q}(n)$	orthogonal matrix
$\mathbf{R}(n)$	upper triangular matrix or Cholesky factor
$\mathbf{R}^{-1}(n)$	lower triangular matrix or inverse Cholesky factor
$\mathbf{s}$	desired signal vector
$\mathbf{S}(n)$	information matrix in Kalman filter
$\mathbf{S}^{-1}(n)$	correlation matrix in Kalman filter
$\mathbf{w}(n)$	weight vector of combining process
$\mathbf{w}_{\mathrm{unc}}(n)$	unconstrained weight vector
$y(n)$	combining output of MC-CDMA receiver
$\mathbf{z}(n)$	original input data vector
$\tilde{\mathbf{z}}(n)$	new input data vector for CM criterion
$\tilde{\mathbf{Z}}(n)$	new input data matrix for CM criterion
$\Gamma(n)$	intermediate matrix denoted by $\Gamma(n) = \mathbf{S}(n)\mathbf{C}$
$\Lambda^{1/2}(n)$	diagonal matrix constructed by forgetting factor
$\Phi(n)$	intermediate matrix denoted by $\Phi(n) = \mathbf{C}^H\Gamma(n)$
$\Omega(n)$	intermediate matrix denoted by $\Omega(n) = \Gamma(n)\Phi^{-1}(n)$
$\alpha_{k,m}$	overall effects of phase shift and fading for the mth carrier of the kth user
λ	forgetting factor
$\psi(t)$	chip waveform
$\mathbf{0}$	null matrix
$\mathbf{1}$	unity entries vector

multiplexing (OFDM) and CDMA systems [7,11,10,15], is one of the attractive techniques for future wireless communication systems to provide high level of user traffic along a high-quality service. It can be used to overcome the capacity limit of the conventional DS-CDMA system. The basic idea behind the multicarrier system is the division of the available spectrum into sub-bands of relatively narrow bandwidth, such that the sub-channels are nearly distortionless. Besides, it has the advantage that the fast Fourier transform (FFT) can be implemented without increasing the system complexities. Because that the use of the MC-CDMA technique has the advantages of insensitivity to the frequency-selective channel, frequency diversity, and capability of handling diverse multimedia traffics, it has the properties desirable for high data-rate wireless multimedia services. Therefore, the MC-CDMA is an effective technique for high data-rate applications, such as mobile communication and wireless LAN.

The main concern of this paper is to deal with the problem of MAI suppression for MC-CDMA system with combining process, using the adaptive filtering techniques. It is well known that among the members of the RLS family the so-called inverse QRD-RLS (IQRD-RLS) algorithm [2] has better numerical stability and provide the faster convergence rate than the least mean squared (LMS) approaches. Basically, it computes the inverse QR decomposition (or the inverse Cholesky factorization) of the input data matrix using *Givens* rotation and solving the LS weight vector without using the back substitution [2,8]. Since the inverse QR-based approach has the benefit, that is, the rotation-based computations are easily mapped onto systolic array structures for a parallel implementation with VLSI technology [8]. Moreover, in wireless communication systems, the information of *channel parameters* could not be estimated perfectly, and for convenience, it is referred to as the problem of *channel mismatch*. In such cases, the adaptive filtering algorithm based on the *constant modulus* (CM) criterion is a significant approach [12,16] to circumvent the effect due to channel mismatch. Where CM is the property-restoration approach exploits the fact that many communications signals commonly used to employ transmitted waveforms with certain invariant properties (e.g., constant envelopes). That can be sensed and then used as the basis for adapting a filter. If propagation or interference effects degrade the receiver output or disturb the invariant property, the CM algorithm can be developed to fix this disturbance and adjusts the weights of filter in such a way to restore the invariant property. If the algorithm accomplishes and/or equalizes the channel distortion, then the signal will be corrected, hence, not only the property but also the quality of the receiver's output is improved.

To deal with the MAI problem for MC-CDMA system, many conventional techniques [9,11,19–21] such as the maximal ratio combining (MRC) method, the blind adaptation algorithm, and the constrained optimization approach based on the linearly constrained minimum variance (LCMV) (or minimum output energy; MOE) criterion, have been proposed. Where MRC method is considered to be the optimal solution of the weight vector of the combining process, in the sense of maximizing the output signal to interference and noise ratio (SINR), while noise and interference across different sub-carriers are uncorrelated. This may occur when the additive white Gaussian noise (AWGN) channel is considered. However, if the near-far effect or strong MAI are occurred, it becomes more difficult to estimate the parameters of fading channel. In such cases the system performance will be degraded, accordingly, and the MRC method will not be the optimal approach for suppressing MAI.

To improve the performance the LMS-type blind adaptation algorithms suggested by Lehnert et al. was proposed in [11,21]. It has been employed in the MC-CDMA system for determining the weight vector to achieve the maximum output value of SINR. However, the mirror effect might occur due to the wrong projecting direction of the initial weight vector as discussed in [4] (or see Appendix A). Under such circumstance the use of the blind adaptation approach could seriously degrade the performance, in terms of bit error rate (BER), even though the SINR is still acceptable. In [5], it has been demonstrated that in the DS-CDMA system if the RMS-type blind adaptive algorithm was implemented, along with differential detector, to recover phase information of desired user, the mirror effect could be avoided and thus improving the BER. More discussion on this issue will be given in Section 4.

Next, in [19,20] a constrained optimization approach, based on the LCMV (or minimum output energy; MOE) criterion, was proposed for the multiuser DS-CDMA system. It is implemented by using the partitioned linear interference canceller (PLIC) structure. The advantage of this approach is that only the knowledge of desired user's code sequence and timing are required rather than the code sequences of other users. It also required the information of channel parameters for constructing the constrained matrix in associated with the code sequence of desired user [11,13,20]. This approach can be applied to the MC-CDMA system for multiuser detection. In fact, the linearly constrained CM (LCCM) criterion with gradient algorithm proposed by Miguez et al. [12,13] is the one implemented with the PLIC structure for MC-CDMA system. As described earlier, in general, the technique based on the CM criterion could have better performance against the channel mismatch, due to its invariant property. Although, in [22] Xu and Feng showed that in noise free cases the approach with the LCCM criterion could be employed to completely remove MAI if and only if the desired user's amplitude is no less than the critical value, $1/\sqrt{3}$. However, if the case of fast fading channel environment and near-far effect are considered, the weight vector updated with the gradient-based algorithms might take much iteration to achieve the optimal solution.

To circumvent the drawback described above with the conventional approaches, in this paper, a novel linearly constrained adaptive filtering algorithm is developed. Based on the LCCM least square (LS) criterion, a new robust linearly constrained inverse QRD-RLS (LC IQRD-RLS) algorithm is derived, and is referred to as the LCCM IQRD-RLS algorithm. Basically, it can be viewed as the combination of the CM criterion and the direct constrained optimization along with the IQRD-RLS algorithm. The proposed robust LCCM IQRD-RLS algorithm has the capability to combat the MAI and the problem of channel mismatch, effectively. It is noted that in [3,4] the LC IQRD-RLS algorithm has been successfully employed in the array signal processing for moving jammers suppression, and MAI cancellation for MC-CDMA system, respectively. Therefore, we expect that the LCCM IQRD-RLS algorithm can perform better than the LCCM-gradient algorithm, the LMS-type and RMS-type blind adaptation algorithms associated with differential detector, and the LCMV approach for MAI suppression, when the problem of channel mismatch is considered.

In what follows, the problem description and system model of MC-CDMA with combining process for multiuser detection is first reviewed in Section 2. After that, in Section 3, we introduce the idea of CM LS criterion implemented by the LC IQRD-RLS algorithm and discuss the rationale behind it. Moreover, to avoid the effect due to constrained drift of the weight vector during the adaptation process, the robust version of the LCCM IQRD-RLS algorithm is proposed by adding an extra correcting term according to the projection matrix. In Section 4, computer simulations are carried out to verify the merits, in terms of output SINR and BER, of the proposed robust LCCM IQRD-RLS algorithm for the MC-CDMA system associated with the combining process. Finally, some conclusions are given in Section 5.

2. System model

To proceed with the derivation of the new adaptive algorithm, in this section, the MC-CDMA system with K simultaneous users and M orthogonal carriers is considered. As depicted in Fig. 1(a), the transmitter has a signature sequence $a^{(k)}$ for the kth user and a code sequence $c^{(k)}$ across all carriers. That is, the data stream is spread in the time domain by $a^{(k)}$ and frequency domain by $c^{(k)}$. The signature sequence of the kth user is designated by

$$a^{(k)} = (\ldots, a_0^{(k)}, a_1^{(k)}, \ldots, a_{N-1}^{(k)}, \ldots) \tag{1}$$

where $a_i^{(k)}$, for $i = 0, 1, \ldots, N-1$, are assumed to be independent and identically distribution (i.i.d.) random variables, each of them takes the values of -1 and $+1$ and assumed to be equal probable, i.e., $\Pr(a_i^{(k)} = -1) = \Pr(a_i^{(k)} = 1) = \frac{1}{2}$. The data sequence $b^{(k)}$ of the kth user is denoted as

$$b^{(k)} = (\ldots, b_0^{(k)}, b_1^{(k)}, b_2^{(k)}, \ldots), \tag{2}$$

where the data symbols $b_i^{(k)}$ are assumed to be random variables with $E[|b_j^{(k)}|^2] = 1$, and each data signal is spread by N chips of signature sequences. Such that the transmitted signal of the kth user can be expressed as

$$\sum_{m=1}^{M} \sqrt{2P_k} c_m^{(k)} \left\{ \sum_{i=-\infty}^{\infty} b_{\lfloor i/N \rfloor}^{(k)} a_i^{(k)} \psi(t - iT_c) \right\} e^{j\omega_m t}. \tag{3}$$

In (3), P_k denotes the power of the kth user in each carrier, ω_m is the frequency of the mth carrier, and the parameter $c_m^{(k)}$ is the code signal across the mth carrier branch. We assume each carrier undergoes independent frequency-nonselective slow Rayleigh fading channel with additive white Gaussian noise (AWGN). Thus, the received signal can be expressed as

$$r(t) = \sum_{k=1}^{K} \sum_{m=1}^{M} \sqrt{2P_k} c_m^{(k)} \left\{ \sum_{i=-\infty}^{\infty} b_{\lfloor i/N \rfloor}^{(k)} a_i^{(k)} \times \psi(t - T_k - iT_c) \right\} \cdot e^{j\omega_m (t - T_k)} \alpha_{k,m} + n(t). \tag{4}$$

Parameter $\alpha_{k,m}$ accounts for the overall effects of phase shift and fading for the mth carrier of the kth user, T_k is the relative delay of the kth user, and $n(t)$ is the zero-mean complex Gaussian noise. For $k = 1, 2, \ldots, K$ and $m = 1, 2, \ldots, M$, $\alpha_{k,m}$ can be modeled as complex i.i.d. Gaussian random variables with zero-mean, so that the amplitude of each carrier is Rayleigh distributed. Besides, for synchronizing receiver and assumed that the first user is the desired user, T_1 is set to null, and the energy of the band-limited chip waveform is normalized to T_c, i.e., $\int_{-\infty}^{\infty} |\psi(t)|^2 \, dt = T_c$, where T_c is denoted as chip duration and the carrier frequencies are well separated so that adjacent frequency bands do not interfere with each other.

Since the MC-CDMA system provides the frequency diversity to mitigate the frequency-selective fading channel caused by multipath effect, an

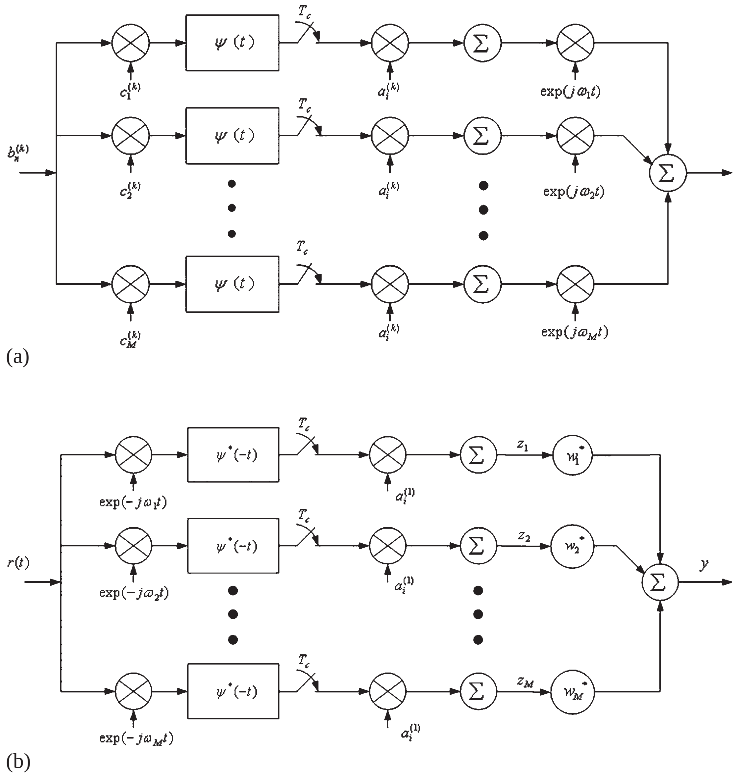

Fig. 1. (a) The MC-CDMA transmitter system model of kth user. (b) The MC-CDMA receiver with combining process for user 1 (desired user).

appropriate combing method is necessary and plays an important role for the performance of detection process. As shown in Fig. 1(b), a M-dimensional weight vector $\mathbf{w} = [w_1, w_2, \ldots, w_M]^{\mathrm{T}}$ is adjusted adaptively to combine the contribution from the M branches, then, gives the decision statistic for executing symbol-by-symbol detection. If the transmitted data is $b_0^{(1)}$, the output of the combiner of the mth branch due to the first desired user is

$$s_m = b_0^{(1)} \sqrt{2P_1} N T_c c_m^{(1)} \alpha_{1,m} \tag{5}$$

and the output signal of the mth branch from the kth user, for $k \geqslant 2$, is expressed as

$$i_{k,m} = \sqrt{2P_k} c_m^{(k)} \mathrm{e}^{-\mathrm{j}\omega_m T_k} \alpha_{k,m} \cdot \sum_{i=0}^{N-1} \sum_{\lambda=-\infty}^{\infty} b_{\lfloor \lambda/N \rfloor}^{(k)} a_i^{(1)} a_\lambda^{(k)} \hat{\psi}((i-\lambda)T_c - T_k), \tag{6}$$

where chip waveform $\hat{\psi}(t) = \int_{-\infty}^{\infty} \psi(s)\psi^*(s-t)\,\mathrm{d}s$ is the output after the chip-matched filter. The overall output of the accumulator, in $M \times 1$ vector form, is given by

$$\mathbf{z} = \mathbf{s} + \mathbf{n} + \sum_{k=2}^{K} \mathbf{i}_k. \tag{7}$$

In (7), desired signal vector is denoted as $\mathbf{s}$, $\mathbf{n} = [n_1 \;\; n_2 \;\; \ldots \;\; n_M]^{\mathrm{T}}$ is the vector corresponding to the background noise, and vector $\mathbf{i}_k = [i_{k,1} \;\; i_{k,2} \;\; \ldots \;\; i_{k,M}]^{\mathrm{T}}$ contains the components of multiple access interference due to other users. The goal of combining process is to determine an optimal weight vector, $\mathbf{w}$, to extract the desired signal vector $\mathbf{s}$ of (7).

3. Linearly constrained CM IQRD-RLS algorithm for MC-CDMA detector

In this section, we will develop a new robust linearly constrained IQRD-RLS algorithm based on

LCCM LS criterion. Where the constrained optimal weight vector is derived with direct constrained approach, and is quite different from the LCCM gradient-type algorithm addressed in [12], with the PLIC structure, which is an indirect constrained approach. To do so, we first introduce the unconstrained CM with IQRD-RLS algorithm before we derive its constrained counterpart.

3.1. Unconstrained CM with IQRD-RLS algorithm

In Fig. 1(b), the receiver of the MC-CDMA system with the combining process is depicted. Where the outputted signal of the combining output is designated by $y(i) = \mathbf{w}^H(i)\mathbf{z}(i)$. For CM approach the outputted signal, $y(i)$, is with constant envelope, e.g., $|y(i)|^2 = A$ (or simply set $A = 1$). The cost function for obtaining the optimal weight vector of combining process is denoted by the weighted least square value of the error, where error signal is defined as $e(i) = 1 - |y(i)|^2$, i.e.,

$$J(n) = \sum_{i=1}^{n} \lambda^{n-i}|e(i)|^2 = \sum_{i=1}^{n} \lambda^{n-i}|1 - |y(i)|^2|^2 \quad \text{(8a)}$$

$$= \sum_{i=1}^{n} \lambda^{n-i}|1 - y^*(i)\mathbf{w}^H(n)\mathbf{z}(i)|^2$$

$$= \sum_{i=1}^{n} \lambda^{n-i}|1 - \mathbf{w}^H(n)\tilde{\mathbf{z}}(i)|^2, \quad \text{(8b)}$$

where the parameter λ is a forgetting factor, which controls the speed of convergence and tracking capability of the algorithm. In order to apply the LC IQRD-RLS algorithm developed in [3,4] to (8b) a new intermediate input data vector $\tilde{\mathbf{z}}(n) = y^*(n)\mathbf{z}(n)$ is introduced, where the weight vector is embedded in $\tilde{\mathbf{z}}(n)$, for CM LS criterion. The matrix form of (8) is given by

$$J(n) = \|\mathbf{\Lambda}^{1/2}(n)\mathbf{e}(n)\|^2$$

$$= \|\mathbf{\Lambda}^{1/2}(n)\mathbf{1} - \mathbf{\Lambda}^{1/2}(n)\tilde{\mathbf{Z}}(n)\mathbf{w}(n)\|^2, \quad (9)$$

where the diagonal weighted matrix and error vector are designated as $\mathbf{\Lambda}^{1/2}(n) = \mathrm{diag}[\sqrt{\lambda^{n-1}}, \sqrt{\lambda^{n-2}}, \ldots, \sqrt{\lambda}, 1]$ and $\mathbf{e}(n) = [e(1), e(2), \ldots, e(n)]^{\mathrm{T}}$, respectively. Moreover, $\mathbf{1} = [1, 1, \ldots, 1]^{\mathrm{T}}$ is an $n \times 1$ unit vector, with its entries being unities, and the new $n \times M$ data matrix corresponding to $\tilde{\mathbf{z}}(n)$ is defined as $\tilde{\mathbf{Z}}(n) = [\tilde{\mathbf{z}}(1), \tilde{\mathbf{z}}(2), \ldots, \tilde{\mathbf{z}}(n)]^{\mathrm{T}}$. As in the conventional QRD-RLS algorithm [8], an orthogonal matrix $\mathbf{Q}(n)$ can be employed to perform the triangular factorization of the weighted data matrix $\mathbf{\Lambda}^{1/2}(n)\tilde{\mathbf{Z}}(n)$ (QR-decomposition), via *Givens* rotation, that is

$$\mathbf{Q}(n)\mathbf{\Lambda}^{1/2}(n)\tilde{\mathbf{Z}}(n) = \begin{bmatrix} \mathbf{R}(n) \\ \mathbf{O} \end{bmatrix}, \quad (10)$$

where $\mathbf{R}(n)$ is an $M \times M$ upper triangular matrix, and $\mathbf{O}$ is a $(n - M) \times M$ null matrix. Similarly, by applying the orthogonal matrix $\mathbf{Q}(n)$ to the weighted unity entries vector, $\mathbf{\Lambda}^{1/2}(n)\mathbf{1}$, of (9) we obtain

$$\mathbf{Q}(n)\mathbf{\Lambda}^{1/2}(n)\mathbf{1} = \begin{bmatrix} \mathbf{a}(n) \\ \mathbf{b}(n) \end{bmatrix}, \quad (11)$$

where $\mathbf{a}(n)$ and $\mathbf{b}(n)$ are the $M \times 1$ and $(n - M) \times 1$ vectors. In consequence, the cost function of (9) can be rewritten by

$$J(n) = \left\| \begin{bmatrix} \mathbf{a}(n) - \mathbf{R}(n)\mathbf{w}(n) \\ \mathbf{b}(n) \end{bmatrix} \right\|^2. \quad (12)$$

The minimum norm solution of (12) is the optimal weight vector of the CM LS solution based on QR-decomposition and is given by

$$\mathbf{w}(n) = \mathbf{R}^{-1}(n)\mathbf{a}(n). \quad (13)$$

Proceed in a similar way as in [2] a modified version of the conventional IQRD-RLS algorithm can be derived, and is referred to as the CM IQRD-RLS algorithm:

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \frac{\mathbf{g}(n)}{t(n)} e(n, n-1). \quad (14)$$

We recall that in practical implementation, vector $\mathbf{g}(n)$ and the scalar parameter $t(n)$ are evaluated via *Givens* rotations, when the inverse upper triangular matrix, $\mathbf{R}^{-1}(n)$ is updated from the $\mathbf{R}^{-1}(n-1)$ by orthogonal transformation. Also, in (14) the priori error and other corresponding parameters are defined by

$$e(n, n-1) = 1 - \mathbf{w}^H(n-1)\tilde{\mathbf{z}}(n) \quad (15)$$

$$\tilde{\mathbf{z}}(n) = y^*(n, n-1)\mathbf{z}(n) \quad (16)$$

and

$$y(n,n-1) = \mathbf{w}^H(n-1)\mathbf{z}(n). \tag{17}$$

As indicated in [2], the adaptation gain (or *Kalman gain*) is denoted as $\mathbf{k}(n) = \mathbf{g}(n)/t(n)$. It is notice that to simplify the optimization of obtaining the CM IQRD-RLS algorithm with the CM LS criterion, some modification has been made. That is, the weight vector, $\mathbf{w}(n)$, embedded in the new intermediate input data vector $\tilde{\mathbf{z}}(n) = (\mathbf{w}^H(n)\mathbf{z}(n))^*\mathbf{z}(n)$, has been replaced by the priori weight vector, $\mathbf{w}(n-1)$ as defined in (16) and (17). Indeed, it can be viewed as an iterative optimization approach. This kind of approach happened very often when deal with the problem, such as the iterative quadratic maximum likelihood (IQML) described in [1,14] for frequency estimation and beamforming problems. After doing this modification and some mathematical manipulation, the exponential weighted cost function can be rewritten as (8b). Based on (8b) similar approach as conventional LS criterion can be performed to obtain the CM IQRD-RLS algorithm. To distinguish with the linearly constrained (LC) CM IQRD-RLS algorithm, which will be developed in what follows, (14) is referred to as the unconstrained CM IQRD-RLS algorithm. Such that with the parameter of *Kalman gain* (14) can be expressed as

$$\mathbf{w}_{\text{unc}}(n) = \mathbf{w}_{\text{unc}}(n-1) + \mathbf{k}(n)e_{\text{unc}}(n,n-1) \tag{18}$$

with

$$e_{\text{unc}}(n,n-1) = 1 - \mathbf{w}^H_{\text{unc}}(n-1)\tilde{\mathbf{z}}(n). \tag{19}$$

3.2. Direct linearly constrained CM with IQRD-RLS algorithm

Before we go any further, it should be noted that one of the shortcomings of CM criterion is that it may capture interference rather than the desired signal, when the interference has power much larger than the desired signal. An appropriate constraint corresponding to the desired signal should be considered to avoid the capturing problem. Under such consideration, a constraint matrix is constructed and added to the cost function of (8). That is, the cost function is minimized subject to a linear constraint, i.e.,

$$\min J(n) \text{ subject to } \mathbf{C}^H\mathbf{w}(n) = \mathbf{f}, \tag{20}$$

where $\mathbf{C}$ is a $M \times P$ constraint matrix, whose columns specify the constraints, and $\mathbf{f}$ is a $P \times 1$ response vector of constraint value, with parameter P being the number of specified constraints.

To develop the linearly constrained IQRD-RLS (LC IQRD-RLS) algorithm, based on the LCCM LS criterion, first we have to derive the direct optimal weight vector of (20) by using the Lagrange multiplier method. Follow the similar procedure of [3]; we derive the optimal solution of the LCCM LS weight vector, with the notation of inverse QR-decomposition, i.e.,

$$\begin{aligned}\mathbf{w}(n) = {} & \mathbf{R}^{-1}(n)\mathbf{a}(n) + [\mathbf{R}^H(n)\mathbf{R}(n)]^{-1} \\ & \times \mathbf{C}\{\mathbf{C}^H[\mathbf{R}^H(n)\mathbf{R}(n)]^{-1}\mathbf{C}\}^{-1} \\ & \times [\mathbf{f} - \mathbf{C}^H\mathbf{R}^{-1}(n)\mathbf{a}(n)]\end{aligned} \tag{21}$$

or

$$\begin{aligned}\mathbf{w}(n) = {} & \mathbf{w}_{\text{unc}}(n) + [\mathbf{R}^H(n)\mathbf{R}(n)]^{-1} \\ & \times \mathbf{C}\{\mathbf{C}^H[\mathbf{R}^H(n)\mathbf{R}(n)]^{-1}\mathbf{C}\}^{-1} \\ & \times [\mathbf{f} - \mathbf{C}^H\mathbf{w}_{\text{unc}}(n)].\end{aligned} \tag{22}$$

Similarly, to derive the recursive implementation of (22), in terms of constrained weight vector, $\mathbf{w}(n)$, we define a new $M \times M$ matrix $\mathbf{S}(n)$:

$$\mathbf{S}(n) = \mathbf{R}^{-1}(n)\mathbf{R}^{-H}(n). \tag{23}$$

It can be easily shown that matrix $\mathbf{S}^{-1}(n)$ is equivalent to the following definition

$$\begin{aligned}\mathbf{S}^{-1}(n) &= \tilde{\mathbf{Z}}^H(n)\mathbf{\Lambda}(n)\tilde{\mathbf{Z}}(n) = \sum_{i=1}^{n}\lambda^{n-i}\tilde{\mathbf{z}}(i)\tilde{\mathbf{z}}^H(i) \\ &= \sum_{i=1}^{n}\lambda^{n-i}|y(i)|^2\mathbf{z}(i)\mathbf{z}^H(i) \\ &= \sum_{i=1}^{n}\lambda^{n-i}\mathbf{z}(i)\mathbf{z}^H(i).\end{aligned} \tag{24}$$

We note that to obtain (24), the property $|y(i)|^2 = 1$ has been employed. Moreover, let the parameters $\mathbf{\Gamma}(n)$ and $\mathbf{\Phi}(n)$ be defined as $\mathbf{\Gamma}(n) = \mathbf{S}(n)\mathbf{C}$ and $\mathbf{\Phi}(n) = \mathbf{C}^H\mathbf{\Gamma}(n) = \mathbf{C}^H\mathbf{S}(n)\mathbf{C}$, respectively, (22) can be rewritten by

$$\mathbf{w}(n) = \mathbf{w}_{\text{unc}}(n) + \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}_{\text{unc}}(n)]. \tag{25}$$

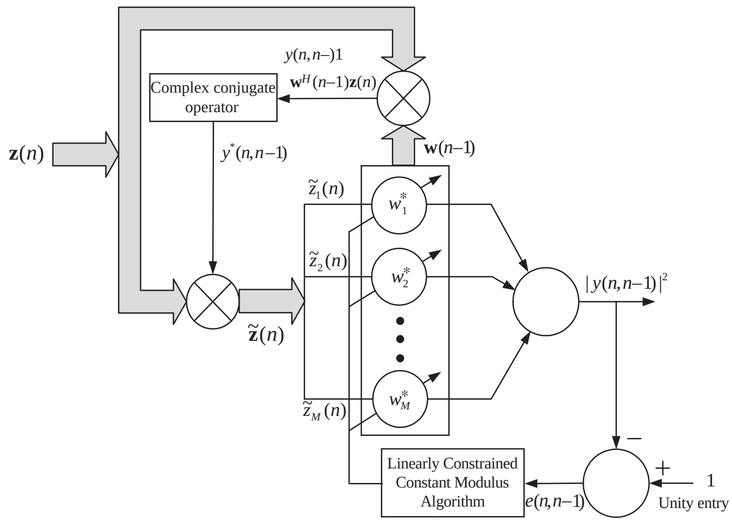

Fig. 2. The block diagram for implementing the LCCM IQRD-RLS algorithm for updating the weight vector $\mathbf{w}(n)$.

By the same procedure as in the *Appendix* of [3], the recursive equation of $\mathbf{R}^{-1}(n)\mathbf{R}^{-H}(n)$ can be derived, but with the new CM version input data vector, $\tilde{\mathbf{z}}(n)$, instead of using the original input vector $\mathbf{z}(n)$. Moreover, based on the definition of $\mathbf{\Gamma}(n)$ and $\mathbf{\Phi}(n)$, the recursive equations can be easily derived

$$\begin{aligned}\mathbf{\Gamma}(n) &= \mathbf{S}(n)\mathbf{C} = \mathbf{R}^{-1}(n)\mathbf{R}^{-H}(n)\mathbf{C} \\ &= \left[\frac{1}{\lambda}\mathbf{R}^{-1}(n-1)\mathbf{R}^{-H}(n-1) - \mathbf{g}(n)\mathbf{g}^H(n)\right]\mathbf{C} \\ &= \lambda^{-1}\mathbf{\Gamma}(n-1) - \mathbf{g}(n)\alpha(n) \qquad (26)\end{aligned}$$

and

$$\begin{aligned}\mathbf{\Phi}(n) &= \mathbf{C}^H\mathbf{S}(n)\mathbf{C} = \mathbf{C}^H\mathbf{R}^{-1}(n)\mathbf{R}^{-H}(n)\mathbf{C} \\ &= \mathbf{C}^H\left[\frac{1}{\lambda}\mathbf{R}^{-1}(n-1)\mathbf{R}^{-H}(n-1) - \mathbf{g}(n)\mathbf{g}^H(n)\right]\mathbf{C} \\ &= \lambda^{-1}\mathbf{\Phi}(n-1) - \alpha^H(n)\alpha(n) \qquad (27)\end{aligned}$$

with the row vector $\alpha(n) = \mathbf{g}^H(n)\mathbf{C}$. Applying the matrix inversion lemma to (27), we have

$$\mathbf{\Phi}^{-1}(n) = \lambda[\mathbf{I} + \sqrt{\lambda}\mathbf{q}(n)\alpha(n)]\mathbf{\Phi}^{-1}(n-1) \qquad (28)$$

with $\mathbf{q}(n)$ being defined by

$$\mathbf{q}(n) = \frac{\sqrt{\lambda}\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)}{1 - \lambda\alpha(n)\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)}. \qquad (29)$$

Finally, by substituting (26) and (28) into (25), we obtain the LCCM IQRD-RLS algorithm for updating the weight vector in the combining process of the MC-CDMA detector, i.e.,

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \rho(n)e(n, n-1) \qquad (30)$$

with

$$\rho(n) = \mathbf{k}(n) - \frac{\sqrt{\lambda}}{t(n)}\mathbf{\Gamma}(n)\mathbf{q}(n), \qquad (31)$$

$$e(n, n-1) = 1 - \mathbf{w}^H(n-1)\tilde{\mathbf{z}}(n). \qquad (32)$$

This completes the derivation of the LCCM IQRD-RLS algorithm for MC-CDMA detector with combining process. Also, the block diagram for updating the weight vector $\mathbf{w}(n)$ by LCCM IQRD-RLS algorithm is depicted in Fig. 2.

3.3. The robust LCCM IQRD-RLS algorithm

To further improve the numerical property and mitigate the effect due to imperfect channel parameters estimation, as indicated in [4], a robust version of the

LCCM IQRD-RLS algorithm could be developed. For convenience to discuss, after some mathematical manipulation, the LCCM IQRD-RLS algorithm of (30) can be rewritten as

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \mathbf{F}(n)\mathbf{k}(n)e(n,n-1) \tag{33}$$

with

$$\mathbf{F}(n) = \mathbf{I}_M - \boldsymbol{\Gamma}(n)\boldsymbol{\Phi}^{-1}(n)\mathbf{C}^H. \tag{34}$$

Here $\mathbf{F}(n)$ can be viewed as a projection operator. In fact, (33) has a similar form as the gradient-projection algorithm [6], in which, due to *round-off error*, the weight vector may not satisfy the constraints after a number of iterations. To compensate this effect, we may simply follow the approach similar to [18], to obtain the modified version of the LCCM IQRD-RLS algorithm. To do so we add an extract correcting term proportional to the *drift* of constraint $[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n)]$, i.e.,

$$\begin{aligned}\mathbf{w}(n) = {} & \mathbf{w}(n-1) + \mathbf{F}(n)\mathbf{k}(n)e(n,n-1) \\ & + \boldsymbol{\Gamma}(n)\boldsymbol{\Phi}^{-1}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n-1)].\end{aligned} \tag{35}$$

We note that if the weight vector satisfies the constraint, $[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n)]$, the correcting term (the *third term* on the right side of (35)) will vanish. Let $\boldsymbol{\Omega}(n) = \boldsymbol{\Gamma}(n)\boldsymbol{\Phi}^{-1}(n)$ and from *Appendix B*, we obtain the robust version of the LCCM IQRD-RLS algorithm to update weight vector

$$\begin{aligned}\mathbf{w}(n) &= \mathbf{w}(n-1) + \mathbf{F}(n)\mathbf{k}(n)e(n,n-1) \\ &\quad + \boldsymbol{\Gamma}(n)\boldsymbol{\Phi}^{-1}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n-1)] \\ &= \mathbf{w}'(n-1) + \boldsymbol{\Omega}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}'(n-1)],\end{aligned} \tag{36}$$

where $\mathbf{w}'(n-1)$ is defined by

$$\mathbf{w}'(n-1) = \mathbf{w}(n-1) + \mathbf{k}(n)e(n,n-1). \tag{37}$$

It represents that the weight vector with round off error accumulation. In (36) $\boldsymbol{\Omega}(n)$ was defined in (B.3) and can be updated recursively using (B.5). This completes the derivation of the robust LCCM IQRD-RLS algorithm with the initial values

$$\boldsymbol{\Omega}(0) = \boldsymbol{\Gamma}(0)[\mathbf{C}^H\boldsymbol{\Gamma}(0)]^{-1} \tag{38}$$

and

$$\mathbf{w}(0) = \boldsymbol{\Omega}(0)\mathbf{f}. \tag{39}$$

Table 1
Summary of the robust LCCM IQRD-RLS algorithm

- Initialization: $\mathbf{R}^{-1}(0) = \delta^{-1}\mathbf{I}$,
  δ = small positive constant

  $\boldsymbol{\Gamma}(0) = \mathbf{R}^{-1}(0)\mathbf{R}^{-H}(0)\mathbf{C}$,

  $\boldsymbol{\Omega}(0) = \boldsymbol{\Gamma}(0)[\mathbf{C}^H\boldsymbol{\Gamma}(0)]^{-1}$

  $\mathbf{w}(0) = \boldsymbol{\Omega}(0)\mathbf{f}$
- For $n = 1, 2, \ldots,$ do
  1. The new data vector is transformed by

     $\tilde{\mathbf{z}}(n) = y(n,n-1)\mathbf{z}(n)$
  2. Compute the intermediate vector $\mathbf{x}(n)$

     $$\mathbf{x}(n) = \frac{\mathbf{R}^{-H}(n-1)\tilde{\mathbf{z}}(n)}{\sqrt{\lambda}}$$
  3. Evaluate the rotations that define $\mathbf{P}(n)$ which annihilates vector $\mathbf{x}(n)$ and compute the scalar variable $t(n)$

     $$\mathbf{P}(n)\begin{bmatrix}\mathbf{x}(n)\\ 1\end{bmatrix} = \begin{bmatrix}\mathbf{o}\\ t(n)\end{bmatrix}$$
  4. Update the lower triangular matrix $\mathbf{R}^{-H}(n)$ and compute the vector $\mathbf{g}(n)$ and $\alpha(n) = \mathbf{g}^H(n)\mathbf{C}$

     $$\mathbf{P}(n)\begin{bmatrix}\lambda^{-1/2}\mathbf{R}^{-H}(n-1)\\ \mathbf{o}^{\mathrm{T}}\end{bmatrix} = \begin{bmatrix}\mathbf{R}^{-H}(n)\\ \mathbf{g}^H(n)\end{bmatrix}$$
  5. The Kalman gain was evaluated by

     $$\mathbf{k}(n) = \frac{\mathbf{g}(n)}{t(n)}$$
- Update following equations and intermediate inverse matrix:

  $\mathbf{u}(n) = \mathbf{C}^H\mathbf{k}(n)$ and $\mathbf{v}^H(n) = \tilde{\mathbf{z}}^H(n)\boldsymbol{\Omega}(n-1)$

  $$\boldsymbol{\Omega}'(n) = [\boldsymbol{\Omega}(n-1) - \mathbf{k}(n)\mathbf{v}(n)] \cdot \left[\mathbf{I}_P + \frac{\mathbf{u}(n)\mathbf{v}^H(n)}{1 - \mathbf{v}^H(n)\mathbf{u}(n)}\right]$$

  $$\boldsymbol{\Omega}(n) = \boldsymbol{\Omega}'(n) + \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}[\mathbf{I}_P - \mathbf{C}^H\boldsymbol{\Omega}'(n)]$$
- Updating the weight vector of the robust LCCM IQRD-RLS algorithm

  $$\mathbf{w}(n) = \mathbf{w}'(n-1) + \boldsymbol{\Omega}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}'(n-1)]$$

  with

  $$\mathbf{w}'(n-1) = \mathbf{w}(n-1) + \mathbf{k}(n)e(n,n-1)$$

  $$e(n,n-1) = 1 - \mathbf{w}^H(n-1)\tilde{\mathbf{z}}(n)$$

A complete procedure for implementing the robust LCCM IQRD-RLS algorithm is summarized in Table 1, as reference.

4. Computer simulation results

In this section, computer simulations are carried out to validate and investigate the capability of the proposed algorithm for MAI suppression in the MC-CDMA system with combining process under Rayleigh fading channel. Especially, when the channel mismatch and the near-far environments are considered. To investigate the system performance, the output SINR, output power, and BER are evaluated and compared with the conventional MRC approach, blind adaptation algorithm, constrained LMS algorithm based on PLIC structure and the LCCM-gradient algorithm. Moreover, to model the channel mismatch the discrepancy due to imperfect channel estimation is generated from a Gaussian random generator with zero-mean and variance to be 0.05. In constructing the constrained matrix **C**, the discrepancy just described is added to the ideal values of channel parameters, $\alpha_{1,i}$, for $i = 1, \ldots, M$.

In computer simulation, the forgetting factor used in the LCCM IQRD-RLS algorithm and the number of sub-carrier (branches) in the MC-CDMA system are chosen to be $\lambda = 0.995$ and 8, respectively. Since only a single constraint corresponding to the desired user is involved, the constraint matrix **C** is reduced to a vector. Which is constructed with the code sequence and channel parameters related to the desired user associated with each subcarrier. In consequence, the response vector **f** is reduced to a scalar value with unity response, i.e.,

$$\mathbf{C} = [\alpha_{1,1}c_1^{(1)}, \alpha_{1,2}c_2^{(1)}, \ldots, \alpha_{1,M}c_M^{(1)}]^H \tag{40}$$

and

$$\mathbf{f} = 1. \tag{41}$$

Furthermore, for the purpose of comparison, we define the output SINR to be

$$\mathrm{SINR}_{\mathrm{out}} = \frac{E_\alpha[|\mathbf{w}^H\mathbf{s}|^2]}{E_\alpha[|\mathbf{w}^H(\mathbf{n} + \sum_{k=2}^{K}\mathbf{i}_k)|^2]} \tag{42}$$

or equivalently, we have

$$\mathrm{SINR}_{\mathrm{out}} = \frac{E_\alpha[|\mathbf{w}^H\mathbf{z}|^2]}{E_\alpha[|\mathbf{w}^H(\mathbf{n} + \sum_{k=2}^{K}\mathbf{i}_k)|^2]} - 1 = \frac{\mathbf{w}^H\mathbf{R}_z\mathbf{w}}{\mathbf{w}^H\mathbf{R}_{ni}\mathbf{w}} - 1 \tag{43}$$

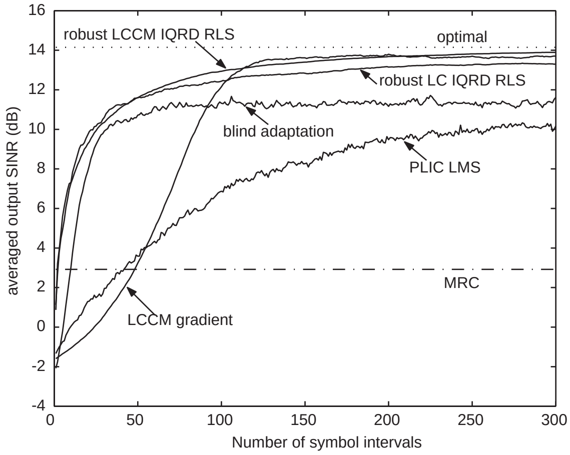

Fig. 3. Performance comparison of output SINR with different techniques under fading channel with a strong interferer 40 dB larger than the desired user (without mismatch case).

where $E_\alpha[.]$ denotes the conditional expectation while $\alpha_{k,m}$ is given. The matrix $\mathbf{R}_{ni}$ in (43), is the correlation matrix constructed by the background noise and interference, and it can be estimated using the method suggested in [11]. Besides, the results of evaluating the BER are the average of 100 independent runs, and in each run 10^4 bits are employed. Moreover, for fairly comparison, the BER is determined after letting all the algorithms converge. Before, we discuss the case of mismatch we will first examine the environment with perfect channel estimation.

4.1. Without mismatch case

For perfect channel estimation the constraint matrix can be constructed perfectly. In this case, the attention is focused on the capability of MAI suppression with near/far effect under the fading channel. To do so, we assume that one of the users has the transmitted power 40 dB stronger than the desired user, and the desired value of SINR is about 15 dB. First, we would like to investigate the capability of MAI suppression, in terms of SINR and BER, with the proposed algorithm. The results are given in Figs. 3 and 4, respectively. From Fig. 3, we observed that the proposed robust LCCM IQRD-RLS algorithm performed the best and having the fastest convergence rate to reach the maximum output SINR. Moreover, in the steady state the

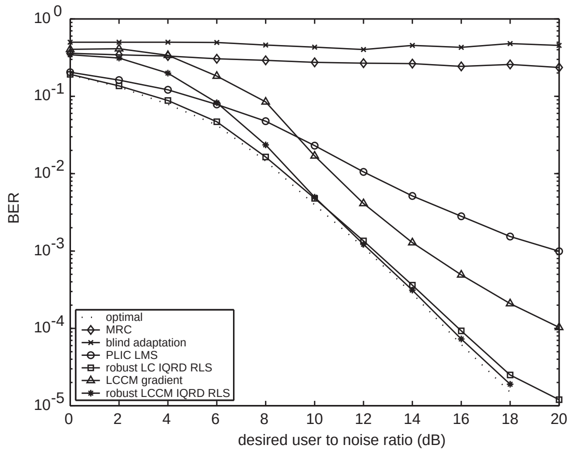

Fig. 4. Performance comparison of BER with different techniques under fading channel with the same parameters as in Fig. 3.

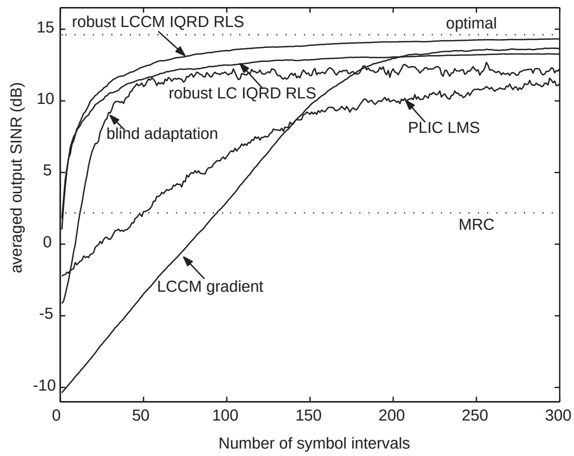

Fig. 5. Performance comparison of output SINR with different techniques under fading channel with a strong interferer 40 dB larger than the desired user (mismatch case).

value of SINR with the robust LCCM IQRD-RLS algorithm is only 0.5 dB less than the maximum value of SINR (ideal value). Also, in this case, the robust LC IQRD-RLS algorithm proposed in our previous work [4] performed similar to the one with the robust LCCM IQRD-RLS algorithm. It means that with perfect channel estimation, the improvement with the CM approach is less significant. Moreover, although with the LCCM-gradient algorithm the value of SINR in the steady state is as good as the proposed algorithm, but due to the inherent property of the gradient-based approach, it converges slower in the transient state.

Next, as indicated in [11] and as shown in Fig. 3, we observed that the LMS-type blind adaptation algorithm outperforms the PLIC-LMS algorithm with relatively higher SINR, and is still 2 dB less than the robust LCCM IQRD-RLS algorithm. With the same parameters as in Fig. 3, in Fig. 4 the performance in terms of BER is investigated with different approaches. Since in this case after 300 iterations (or bits) the steady state could be achieved, the BER is determined after 300 bits. Except, the LMS-type blind adaptation algorithm, the BER in Fig. 4 with various methods is consistent with the SINR shown in Fig. 3 indicated earlier. Also, as expected the approach with the MRC is affected significantly by the MAI when the near-far effect exists. However, due to the *mirror effect* addressed in [4] (or see Appendix A), as observed from Fig. 4 the significant performance degradation in terms of BER could be much serious than the PLIC-LMS algorithm. That is, the LMS-type blind adaptation algorithm has significant performance degradation in terms of BER due to the mirror effect. This phenomenon is caused by opposite projecting direction of weight vector and results in half probability to make wrong decision. Although, as described in [5], for the DS-CDMA system if the RMS-type blind adaptive algorithm was implemented along with differential detector to recover phase information of desired user, the mirror effect could be avoided and thus improving the BER. However, the performance improvement is still not good enough as compared with the proposed LCCM IQRD-RLS algorithm as evident from Fig. 4. We will give more discussion on this issue for the case when the channel mismatch is considered.

4.2. Mismatch case

In practical application, the channel estimation could not be performed without error; therefore, the problem of channel mismatch should be taken into consideration. First, we would like to evaluate the performance, in terms of SINR and the output power, the results are shown in Figs. 5 and 6, respected. As in the mismatch case, from Fig. 5 we found that the

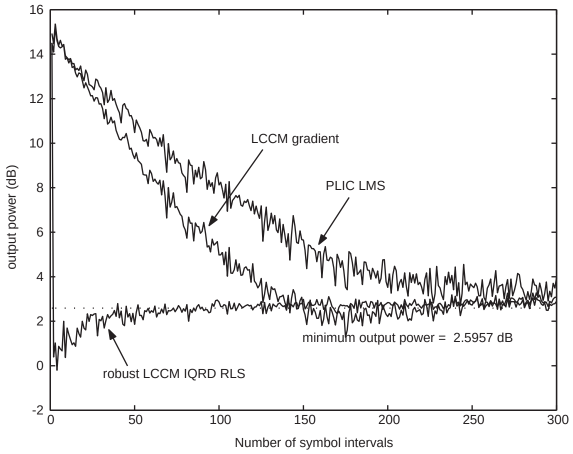

Fig. 6. Performance comparison of output power with different techniques under fading channel with the same parameters as in Fig. 5.

robust LCCM IQRD-RLS algorithm outperformed other methods. It has the largest steady-state output SINR and faster convergence rate approaching to the optimal value. On the other hand, the convergence speed with other methods becomes slower compared with the case without mismatch, as depicted in Fig. 3. This is especially true when the LCCM-gradient algorithm is employed in the MC-CDMA receiver. Similar results were observed in Fig. 6, when the output power is considered as the performance index.

Next, we would like to examine the performance in terms of BER with the parameters to be the same as in Fig. 5. From Fig. 7, we learn that the robust LCCM IQRD-RLS algorithm outperformed other conventional methods, and the BER is very closed to the optimal result. Moreover, in this case with the robust LC IQRD-RLS algorithm proposed in [4] and the PLIC-LMS algorithm [19], both were derived based on the constrained MOE criterion, the performance might degrade, dramatically, when the discrepancy of channel estimation occurred. Especially, when SNR is greater than 12 dB, this is because that the desired signal cancellation and noise enhancement might easily occur in higher SNR environment. However, with the approaches based on the CM criterion, viz., the robust LCCM IQRD-RLS and LCCM-gradient algorithms, the performance is more stable, the impact due to channel mismatch is less significant compared with the methods using other criterion.

Next, it is of interest to comment on the blind adaptation algorithms, viz., the LMS-type [11,21] and the RMS-type [5], implemented with differential detector to recover phase information of desired user, based on the maximum SINR (or MSIR). In [5] for the DS-CDMS system, the RMS-type blind adaptation algorithm with differential encoder has been employed to avoid the mirror effect and improving the BER. It could be used to emphasize the correlation in two adjacent bits, it implied that the angle between initial weight vector in the detection process and desired user's signal could not be greater than 90°. Hence, the mirror effect might not occur, and leads to improve the BER, when it is compared with the LMS-type blind adaptation algorithm with differential encoder. In fact, the optimal weight vector was solved by updating the weight vector with the RMS-type blind adaptation algorithm (with M' times of re-circulation), as described in Table 1 of [5]. The implementation involved the chosen parameters, $c[m,m']$, $m' = 1,2,\ldots,M',\mu$, and updating the projection matrix $\mathbf{P}[m]$. Where $c[m,m']$ for the RMS-type [5] or $c[m]$ in the LMS-type [11,21] blind adaptation algorithm, is chosen to stabilize the algorithm, with the condition of weight vector to have unit norm, during each iteration. It is noted that to update the projection matrix, $\mathbf{P}[m]$, the correlation matrix of received signal has to be estimated for updating the weight vector, with properly selection of forgetting factor, γ. Therefore, the overall computational load of the RMS-type blind adaptation algorithm is much more than the one with the LMS-type, and is highly depending on the number of re-circulation (M'). The larger the M' more performance improvement can be achieved, with extra computation time.

In Fig. 8 and Fig. 9, we have shown the results, in terms of SINR and BER, using the RMS-type algorithm with parameters, $\tilde{M} = 2$, $M' = 2$ or 4, $\gamma = 0.995$ and $\hat{\mu} = 1$ (see Table 1 of [5]), for comparison. Under the case of channel mismatch, we have parameters to be the same as before, except that the power of strong interference is replaced by 20 dB. First, from Fig. 8, we learned that the proposed LCCM IQRD-RLS algorithm has faster convergence rate approaching the optimal solution than other techniques. Also, the RMS-type algorithm with $M' = 4$ (4 times of re-circulations) converges much faster than the

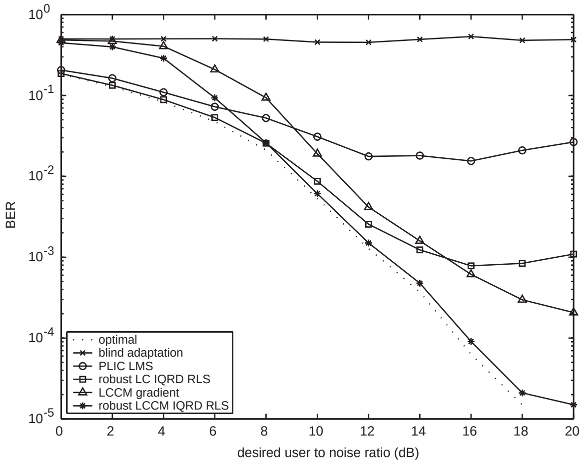

Fig. 7. Performance comparison of BER with different techniques under fading channel with the same parameters as in Fig. 5.

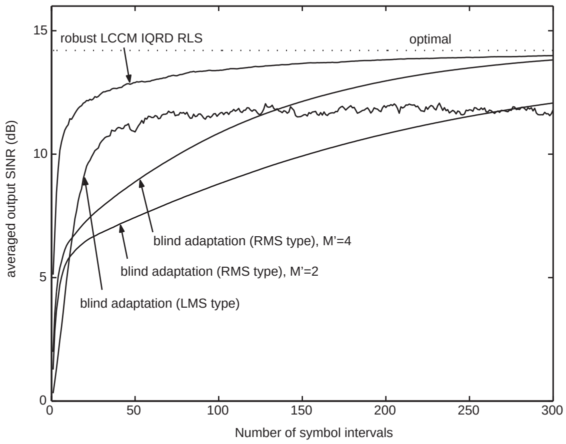

Fig. 8. Performance comparison of the robust LCCM IQRD-RLS algorithm and blind adaptive approaches (LMS-type and RMS-type), in terms of output SINR, under fading channel with a strong interferer 20 dB larger than the desired user (mismatch case).

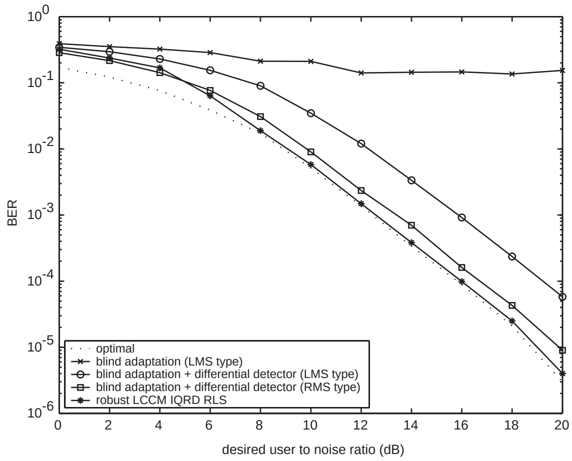

Fig. 9. Performance comparison of BER with different techniques, including the LMS-type and RMS-type blind adaptive algorithms with differential detector under fading channel with the same parameters as in Fig. 8.

one with $M' = 2$. That is, with more iteration (more re-circulation) in each symbol period, the weight vector could converge much closer to the optimal weight vector. However, as indicated in [5], the value of the forgetting factor (γ), used for estimating the correlation matrix, will highly affect the overall convergence rate of the RMS-type algorithm. In practice, it should be selected properly, and the trade off between the performance and the convergence rate has to be considered. Moreover, as evident from Fig. 9, the performance of LMS-type blind adaptation algorithm with differential detector did improve the BER compared with the same algorithm without using differential detector, but, with the paid of requiring extra encoder and decoder to perform differentially coherent detection. Also, with the RMS-type blind adaptation algorithm, the BER performance is improved as shown in Fig. 9, where the estimation of the projection and

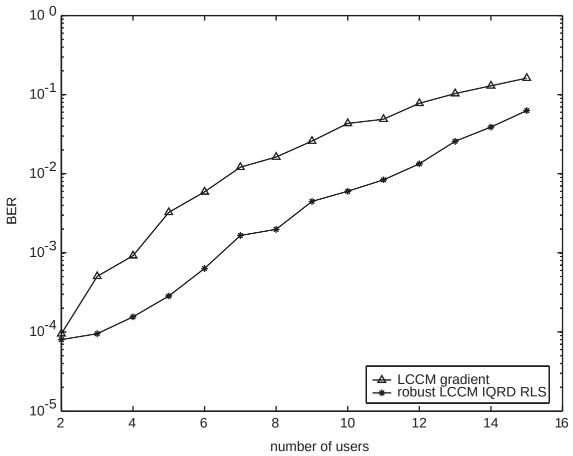

Fig. 10. Performance comparison of BER with the robust LCCM IQRD-RLS algorithm and LCCM-gradient approach under fading channel each user has power 20 dB larger than the desired user (mismatch case).

the correlation matrices have to be performed, hence results in increasing the overall computational complexity compared with the LMS-type algorithm. In fact, the performance degradation of BER with the RMS-type blind adaptation algorithm for $M' = 4$ is 1–2 dB compared with the optimal solution. However, the BER performance with the proposed LCCM IQRD-RLS algorithm could achieve the optimal solution and outperformed the others.

In the last case, the performance of BER versus number of user for both CM based algorithms is investigated. To be more specific, we assume that each user has power 20 dB stronger than the desired user. From Fig. 10, we learn that in all cases with different value of SNR the proposed robust LCCM IQRD-RLS algorithm has superior performance compared with the one using the LCCM-gradient algorithm. Based on the above discussion, we may conclude that the proposed robust LCCM IQRD-RLS algorithm could be used to suppress the MAI, effectively, and achieve desired performance, in terms of output SINR, output power and BER in the MC-CDMA system with stronger interferers. Also, as compared with other existing methods, the proposed LCCM IQRD-RLS algorithm performed more robust against the near/far effect and the problem of channel mismatch, due to imperfect channel estimation.

5. Conclusions

In this paper, we have devised a new robust LCCM IQRD-RLS algorithm for MAI suppression to achieve desired performance in the MC-CDMA system for multiuser detection under fading channel. Before we come to final conclusion, it is of interest to comment on the problem of MAI suppression for MC-CDMA receiver with combining process. Based on the simulation results, we learn that it is not appropriate to use a single performance index to verify the superiority of a specific method. For instance, although, the LMS-type blind adaptation algorithm has relative larger value of output SINR compared with PLIC-LMS algorithm, it does not imply that the BER will be better, as evident from Figs. 3–5 and 7. As described in [5], the differential decoder has to be employed with the LMS-type blind adaptation algorithm to recovering the phase information of desired user, and hence improving the BER performance. To further improve the performance, the RMS-type blind adaptation algorithm could be utilized associated with the differential decoder, with extra paid for the overall computational complexity. As discussed in the previous section, since the proposed LCCM IQRD-RLS algorithm adopted the advantages of the constant modulus criterion and the direct constrained optimization along with the inverse QRD-RLS algorithm. It performed superior to other existing methods, in terms of output SINR, output power and BER, and could be used to alleviate the effect of MAI, effectively, when the near/far effect and the problem of channel mismatch, due to imperfect channel estimation, are considered. Particularly, it is more significant when the algorithm is implemented in limit precision environments. Therefore, it is very suitable to be employed for future wireless multimedia communications to achieve high data-rate transmission.

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Appendix A

In this appendix, to investigate the mirror effect of the blind adaptation algorithm, we recall that the updating equation of the weight vector in [11,21]:

$$\begin{aligned}\mathbf{w}(n) &= h(n)\{\mathbf{w}(n-1) + \mu[\mathbf{z}^H(n)\mathbf{w}(n-1)] \\ &\quad \cdot [(\hat{\mathbf{z}}^H(n)\hat{\mathbf{z}}(n))\mathbf{z}(n) - (\hat{\mathbf{z}}^H(n)\mathbf{z}(n))\hat{\mathbf{z}}(n)]\} \\ &= h(n)\left\{\mathbf{I} + \mu(\hat{\mathbf{z}}^H(n)\hat{\mathbf{z}}(n))\right. \\ &\quad \cdot \left.\left[\mathbf{I}_M - \left(\frac{\hat{\mathbf{z}}(n)\hat{\mathbf{z}}^H(n)}{\hat{\mathbf{z}}^H(n)\hat{\mathbf{z}}(n)}\right)\right]\mathbf{R}_\mathbf{z}(n)\right\}\mathbf{w}(n-1) \\ &= h(n)\{\mathbf{I} - \mu[\mathbf{I} - \mathbf{P}_\mathbf{s}]\mathbf{R}_\mathbf{z}\}\mathbf{w}(n-1), \end{aligned} \tag{A.1}$$

where $\mathbf{P}_\mathbf{s} = \mathbf{s}\mathbf{s}^H/\mathbf{s}^H\mathbf{s}$ is a projection operator to project the received signal onto the desired signal space spanned by $\mathbf{s}$. In what follows, we briefly describe the procedure of [21], where it showed that (A.1) could converge to the optimal solution, by properly choosing the parameter μ. To do so, the matrix $(\mathbf{I} - \mathbf{P}_\mathbf{s})\mathbf{R}_\mathbf{z}$ is first decomposed into

$$(\mathbf{I} - \mathbf{P}_\mathbf{s})\mathbf{R}_\mathbf{z} = \mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^{-1}, \tag{A.2}$$

where $\boldsymbol{\Lambda}$ is a diagonal matrix, whose elements λ_i, $i = 1, 2, \ldots, M$ are eigenvalues of $(\mathbf{I} - \mathbf{P}_\mathbf{s})\mathbf{R}_\mathbf{z}$, and $\mathbf{Q} = [\mathbf{q}_1, \mathbf{q}_2, \ldots, \mathbf{q}_M]$ is an invertible matrix, with $\mathbf{q}_k$ being the eigenvector corresponding to λ_k. Define

$$\mathbf{u}(n) = \mathbf{Q}^{-1}\mathbf{w}(n). \tag{A.3}$$

By substituting (A.1) and (A.2) into (A.3), we have

$$\begin{aligned}\mathbf{u}(n) &= \mathbf{Q}^{-1}h(n)\{\mathbf{I} - \mu\mathbf{Q}\boldsymbol{\Lambda}\mathbf{Q}^{-1}\}\mathbf{w}(n-1) \\ &= h(n)\{\mathbf{I} - \mu\boldsymbol{\Lambda}\}\mathbf{u}(n-1).\end{aligned} \tag{A.4}$$

In [21], it has been shown that after some arrangement of the eigenvalue and its corresponding eigenvector, we have the first eigenvalue $\lambda_1 = 0$ and the corresponding eigenvector will be the optimal weight vector that it maximizes the output SINR. To show this, we refer that since $\lambda_1 = 0$ and if the step size μ is chosen to make $|1 - \mu\lambda_m| < 1$, we have

$$\begin{aligned}\lim_{n\to\infty} u_1(n) &= h\lim_{n\to\infty}(1 - \mu\lambda_1)^n u_1(0) \\ &= hu_1(0) = 1, \quad \text{for } m = 1\end{aligned} \tag{A.5}$$

and

$$\lim_{n\to\infty} u_m(n) = h\lim_{n\to\infty}(1 - \mu\lambda_m)^n u_m(0) = 0, \quad \text{for } m = 2, 3, \ldots, M \tag{A.6}$$

In consequence, we obtain

$$\begin{aligned}\lim_{n\to\infty}\mathbf{w}(n) &= \lim_{n\to\infty}[\mathbf{Q}\mathbf{u}(n)] \\ &= \mathbf{Q}\lim_{n\to\infty}[u_m(n)] \quad \text{for } m = 1, 2, \ldots, M \\ &= \mathbf{q}_1 hu_1(0) = \mathbf{q}_1 = \mathbf{w}_{\text{opt}}.\end{aligned} \tag{A.7}$$

At this point, it is interest to point out that if we consider the opposite sign of the initial weights vector, i.e., $\hat{\mathbf{w}}(0) = -\mathbf{w}(0)$, the initial vector of $\mathbf{u}(n)$ can be expressed as

$$\hat{\mathbf{u}}(0) = \mathbf{Q}^{-1}\hat{\mathbf{w}}(0) = -\mathbf{Q}^{-1}\mathbf{w}(0) = -\mathbf{u}(0) \tag{A.8}$$

then, the weight vector can be obtained

$$\begin{aligned}\lim_{n\to\infty}\hat{\mathbf{w}}(n) &= \lim_{n\to\infty}[\mathbf{Q}\hat{\mathbf{u}}(n)] \\ &= \mathbf{Q}\lim_{n\to\infty}[\hat{\mathbf{u}}_m(n)] \quad \text{for } m = 1, 2, \ldots, M \\ &= \mathbf{q}_1 h(-u_1(0)) = -\mathbf{q}_1 = -\mathbf{w}_{\text{opt}}.\end{aligned} \tag{A.9}$$

The implication of (A.9) is that as illustrated in Fig. 11, if the initial weights vector is not chosen

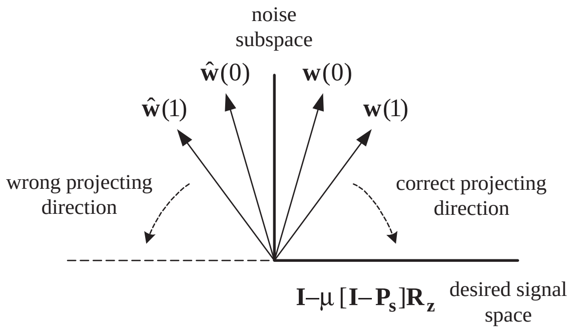

Fig. 11. Interpretation of projecting procedure in blind adaptation algorithm.

properly, it is possible to cause the mirror effect due to the wrong projecting direction. That is, in case the angle between initial weight vector and the desired user's signal is greater than 90 degree, weight vector might update toward the opposite direction of the desired user's signal. Consequently, the detection procedure will make a wrong decision, yields, resulting in having significant performance degradation, in terms of BER.

To avoid the mirror effect, in the recent work [5], the authors demonstrated that the LMS-type blind adaptive algorithm proposed in [11,21] should be implemented by recovering the desired user's phase information. Hence, it needs the phase estimation subsystem to perform the coherent detection. In consequence, the decision bit after the combining process is decoded as

$$\hat{b}_i^{(1)} = \mathrm{sign}\{\mathrm{Re}(y(i)\mathrm{e}^{-\mathrm{j}\hat{\theta}_1})\}, \tag{A.10}$$

where $\hat{\theta}_1$ is the phase estimation of the desired user in the decision variable $y(i)$. However, the phase estimation subsystem will pay lots of effort for finding a properly accurate estimation result. Alternative approach can be employed, which uses the differential detector to recover the desired user's phase information, i.e.,

$$\hat{d}_i^{(1)} = \mathrm{sign}\{\mathrm{Re}(y(i)y(i-1)^*)\} \tag{A.11}$$

with less computational complexity than using the one described in (A.10). Where $\hat{d}_i^{(1)}$ is the estimate of the original data bit $d_i^{(1)} \in \{1,-1\}$, which is differentially encoded with $b_i^{(1)} = b_{i-1}^{(1)} d_i^{(1)}$. The differential encoder can be used to emphasize the correlation in two adjacent bits to prevent the angle between initial weight vector in the detection process and desired user's signal to greater than 90°. By doing so, the mirror effect discussed above can be avoided, and thus enhancing the BER.

Appendix B

In this appendix we would like to simplify (35) and obtain its recursive form. After some simplification, (35) can be rewritten by

$$\begin{aligned}\mathbf{w}(n) &= (\mathbf{I}_M - \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)\mathbf{C}^H)\mathbf{w}(n-1) \\ &\quad + \mathbf{F}(n)\mathbf{k}(n)e(n,n-1) + \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)\mathbf{f} \\ &= \mathbf{F}(n)[\mathbf{w}(n-1) \\ &\quad + \mathbf{k}(n)e(n,n-1)] + \mathbf{m}(n),\end{aligned} \tag{B.1}$$

where vector $\mathbf{m}(n)$ is denoted as $\mathbf{m}(n) = \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)\mathbf{f}$. To further simplify (B.1), we may define a new $M \times P$ matrix as $\mathbf{\Omega}(n) = \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)$ and obtain the recursive relationships between $\mathbf{\Omega}(n)$ and $\mathbf{\Omega}(n-1)$. To do so, we rewrite (28), the recursive expression of $\mathbf{\Phi}^{-1}(n)$, as follows:

$$\begin{aligned}\mathbf{\Phi}^{-1}(n) &= \lambda[\mathbf{I} + \sqrt{\lambda}\mathbf{q}(n)\alpha(n)]\mathbf{\Phi}^{-1}(n-1) \\ &= \lambda\left[\mathbf{\Phi}^{-1}(n-1) + \lambda\frac{\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)\alpha(n)\mathbf{\Phi}^{-1}(n-1)}{1-\lambda\alpha(n)\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)}\right].\end{aligned} \tag{B.2}$$

Applying the results given in (B.2) and (26) to $\mathbf{\Omega}(n)$, and after simplification, it gives

$$\begin{aligned}\mathbf{\Omega}(n) &= \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n) \\ &= \left[\frac{1}{\lambda}\mathbf{\Gamma}(n-1) - \mathbf{g}(n)\alpha(n)\right]\cdot\lambda\left[\mathbf{\Phi}^{-1}(n-1) + \lambda\frac{\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)\alpha(n)\mathbf{\Phi}^{-1}(n-1)}{1-\lambda\alpha(n)\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)}\right] \\ &= [\mathbf{\Gamma}(n-1)\mathbf{\Phi}^{-1}(n-1) - \lambda\mathbf{g}(n)\alpha(n)\mathbf{\Phi}^{-1}(n-1)] \\ &\quad\cdot\left[\mathbf{I}_p + \frac{\lambda\alpha^H(n)\alpha(n)\mathbf{\Phi}^{-1}(n-1)}{1-\lambda\alpha(n)\mathbf{\Phi}^{-1}(n-1)\alpha^H(n)}\right].\end{aligned} \tag{B.3}$$

Moreover, we recalled that the row vector $\alpha(n)$ was defined by

$$\alpha(n) = \mathbf{g}^H(n)\mathbf{C} = \frac{\tilde{\mathbf{z}}^H(n)\mathbf{\Gamma}(n-1)}{\lambda t(n)}. \tag{B.4}$$

Substituting (B.4) into (B.3), we have:

$$\begin{aligned}\mathbf{\Omega}(n) = &\left[\mathbf{\Omega}(n-1) - \lambda\mathbf{g}(n) \times \frac{\tilde{\mathbf{z}}^H(n)\mathbf{\Gamma}(n-1)}{\lambda t(n)}\mathbf{\Phi}^{-1}(n-1)\right] \\ &\cdot \left[\mathbf{I}_P + \frac{\lambda\mathbf{C}^H\mathbf{g}(n)\frac{\tilde{\mathbf{z}}^H(n)\mathbf{\Gamma}(n-1)}{\lambda t(n)}\mathbf{\Phi}^{-1}(n-1)}{1-\lambda\frac{\tilde{\mathbf{z}}^H(n)\mathbf{\Gamma}(n-1)}{\lambda t(n)}\mathbf{\Phi}^{-1}(n-1)\mathbf{C}^H\mathbf{g}(n)}\right] \\ = &[\mathbf{\Omega}(n-1) - \mathbf{k}(n)\mathbf{v}^H(n)] \\ &\cdot \left[\mathbf{I}_P + \frac{\mathbf{u}(n)\mathbf{v}^H(n)}{1-\mathbf{v}^H(n)\mathbf{u}(n)}\right], \qquad \text{(B.5)}\end{aligned}$$

where vectors $\mathbf{u}(n)$ and $\mathbf{v}^H(n)$ are designated as $\mathbf{u}(n) = \mathbf{C}^H\mathbf{k}(n)$ and $\mathbf{v}^H(n) = \tilde{\mathbf{z}}^H(n)\mathbf{\Omega}(n-1)$, respectively. Again, if there is no round off error accumulation and by definition of matrix $\mathbf{\Omega}(n)$ the following equation holds:

$$\begin{aligned}\mathbf{C}^H\mathbf{\Omega}(n) &= \mathbf{C}^H\mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n) \\ &= [\mathbf{C}^H\mathbf{\Gamma}(n)]\cdot[\mathbf{C}^H\mathbf{\Gamma}(n)]^{-1} = \mathbf{I}_P. \qquad \text{(B.6)}\end{aligned}$$

Otherwise, we may denote matrix $\mathbf{\Omega}'(n)$ as the counterpart of $\mathbf{\Omega}(n)$, where the equality of (B.6) is not hold, due to round error accumulation. Again, as in the same manner as in (35), we may introduce an extra correcting term proportional to $[\mathbf{I}_P - \mathbf{C}^H\mathbf{\Omega}'(n)]$, the correcting matrix $\mathbf{\Omega}(n)$, in terms of $\mathbf{\Omega}'(n)$, is given

$$\mathbf{\Omega}(n) = \mathbf{\Omega}'(n) + \mathbf{C}(\mathbf{C}^H\mathbf{C})^{-1}[\mathbf{I}_P - \mathbf{C}^H\mathbf{\Omega}'(n)]. \quad \text{(B.7)}$$

In consequence, from (35), we obtain the robust version of the weight vector updated equation of the proposed algorithm

$$\begin{aligned}\mathbf{w}(n) = &\mathbf{w}(n-1) + \mathbf{F}(n)\mathbf{k}(n)e(n,n-1) \\ &+ \mathbf{\Gamma}(n)\mathbf{\Phi}^{-1}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n-1)] \\ = &\mathbf{w}(n-1) + [\mathbf{I}_M - \mathbf{\Omega}(n)\mathbf{C}^H]\mathbf{k}(n)e(n,n-1) \\ &+ \mathbf{\Omega}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}(n-1)] \\ = &\mathbf{w}(n-1) + \mathbf{k}(n)e(n,n-1) + \mathbf{\Omega}(n) \\ &\times [\mathbf{f} - \mathbf{C}^H(\mathbf{w}(n-1) + \mathbf{k}(n)e(n,n-1))] \\ = &\mathbf{w}'(n-1) + \mathbf{\Omega}(n)[\mathbf{f} - \mathbf{C}^H\mathbf{w}'(n-1)], \quad \text{(B.8)}\end{aligned}$$

where $\mathbf{w}'(n-1)$ is denoted by

$$\mathbf{w}'(n-1) = \mathbf{w}(n-1) + \mathbf{k}(n)e(n,n-1). \qquad \text{(B.9)}$$

It represents that the weight vector is with round off error accumulation. This completes the derivation of the robust LCCM IQRD-RLS algorithm with the initial values

$$\mathbf{\Omega}(0) = \mathbf{\Gamma}(0)[\mathbf{C}^H\mathbf{\Gamma}(0)]^{-1} \qquad \text{(B.10)}$$

and

$$\mathbf{w}(0) = \mathbf{\Omega}(0)\mathbf{f}. \qquad \text{(B.11)}$$

References

[1] M. Agrawal, S. Prasad, Robust adaptive beamforming for wide-band, moving, and coherent jammers via uniform linear arrays, IEEE Trans. Antennas Propag. 47 (8) (August 1999) 1267–1275.

[2] S.T. Alexander, A.L. Ghirnikar, A method for recursive least squares filtering based upon an inverse QR decomposition, IEEE Trans. Signal Processing 41 (1) (January 1993) 20–30.

[3] S.J. Chern, C.Y. Chang, Adaptive linearly constrained inverse QRD-RLS beamforming algorithm for moving jammers suppression, IEEE Trans. Antennas Propag. 50 (8) (August 2002) 1138–1150.

[4] S.J. Chern, C.Y. Chang, T.Y. Liao, Adaptive multiuser interference cancellation with robust constrained IQRD-RLS algorithm for MC-CDMA system, IEEE International Symposium on Intelligent Signal Processing and Communication Systems, Nashville, Tennessee, USA, 20–23 November 2001, pp. 242–246.

[5] J.H. Cho, J.S. Lehnert, Blind adaptive multiuser detection for DS/SSMA communications with generalized random spreading, IEEE Trans. Commun. 49 (6) (June 2001) 1082–1091.

[6] O.L. Frost III, An algorithm for linearly constrained adaptive array processing, Proc. IEEE 60 (8) (August 1972) 926–935.

[7] S. Hara, R. Prasad, Overview of multicarrier CDMA, IEEE Commun. Mag. (December 1997) 126–133.

[8] S. Haykin, Adaptive Filter Theory, 3rd Edition, Englewood Cliffs, NJ, Prentice-Hall, 1996.

[9] M. Honig, U. Madhow, S. Verd'u, Blind adaptive multiuser detection, IEEE Trans. Inf. Theory (July 1995) 944–960.

[10] S. Kondo, L.B. Milstein, Performance of multicarrier DS CDMA systems, IEEE Trans. Commun. 44 (February 1996) 238–246.

[11] T.M. Lok, T.F. Wong, J.S. Lehnert, Blind adaptive signal reception for MC-CDMA systems in Rayleigh fading channels, IEEE Trans. Commun. 47 (3) (March 1999) 464–471.

[12] J. Miguez, L. Castedo, A linearly constrained constant modulus approach to blind adaptive multiuser interference suppression, IEEE Commun. Lett. 2 (8) (August 1998) 217–219.

[13] J. Miguez, L. Castedo, Blind multiuser interference cancellation in multicarrier CDMA: a linearly constrained constant modulus approach, The Ninth IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Vol. 2, 1998, pp. 523–527.

[14] V. Nagesha, S. Kay, On frequency estimation with IQML algorithm, IEEE Trans. Signal Processing 42 (September 1994) 2509–2513.

[15] R.v. Nee, R. Prasad, OFDM Wireless Multimedia Communications, Artech House, 2000.

[16] R. Pickholtz, K. Elbarbary, The recursive constant modulus algorithm; a new approach for real-time array processing, Signals, Systems and Computers, IEEE Conference on Record of The Twenty-Seventh Asilomar, Vol. 1, 1993, pp. 627–632.

[17] J.G. Proakis, Digital Communications, 3rd Edition, McGraw-Hill, New York, 1995.

[18] L.S. Resende, J.T. Romano, M.G. Bellanger, A fast least-squares algorithm for linearly constrained adaptive filtering, IEEE Trans. Signal Processing 44 (5) (May 1996) 1168–1174.

[19] J.B. Schodorf, D.B. Williams, A constraint optimization approach to multiuser detection, IEEE Trans. Signal Processing 45 (1) (January 1997) 258–262.

[20] J.B. Schodorf, D.B. Williams, Array processing techniques for multiuser detection, IEEE Trans. Commun. 45 (11) (November 1997) 1375–1378.

[21] T.F. Wong, T.M. Lok, J.S. Lehnert, M.D. Zoltowski, A linear receiver for direct-sequence spread-spectrum multiple-access systems with antenna arrays and blind adaptation, IEEE Trans. Inf. Theory 44 (March 1998) 659–676.

[22] C. Xu, G. Feng, Comments on: a linearly constrained constant modulus approach to blind adaptive multiuser interference suppression, IEEE Commun. Lett. 4 (9) (September 2000) 280–282.