Blind adaptive algorithm for demodulation of DS/CDMA signals with mismatch

H.-C. Hwang
C.-H. Wei

Abstract: The minimum mean-squared error (MMSE) linear detector is known to be a near–far resistant strategy for direct-sequence code-division multiple access systems. The MMSE linear detector can be implemented adaptively by the MOE adaptation algorithm or the Griffiths' adaptation algorithm, which utilises the desired signal vector for initial adaptation instead of training sequences. The performance loss caused by the imprecise knowledge of the desired signal vector is investigated. A new blind adaptive algorithm is presented to mitigate the effect of the mismatch caused by the timing error in acquisition. Several numerical results show that the new algorithm can provide a resistance to the effect of mismatch compared to the MOE and Griffiths' algorithms.

1 Introduction

In direct-sequence code-division multiple access (DS/CDMA) communication systems, each user transmits the symbol modulated upon a unique spreading sequence. The conventional matched correlator demodulates the transmitted symbol of a specific user by correlating the received signal with a synchronised replica of the spreading waveform of interest [1, 2]. The optimal performance of reception can be achieved only when all spreading waveforms are orthogonal or only one user exists. However, the orthogonal property cannot be easily obtained, owing to random timing offsets between users in an asynchronous system. A nearby interfering user of large power will deteriorate the reception of the highly attenuated signal. The matched correlator is thus vulnerable to the so-called near–far problem, and the system capacity is limited by the multiple access interference (MAI).

The minimum mean-squared error (MMSE) single-user detection technique [3, 4] is known to be an effective strategy for mitigating the near–far problem by utilising the cyclostationarity of the highly structured MAI. This MMSE linear detector can be implemented by training sequences based adaptation algorithms [4] or by the blind adaptation algorithms [5–8]. The blind adaptation algorithms, the minimum output energy (MOE) algorithm and the Griffiths' algorithm, utilise the desired signal vector instead of training sequences for initial adaptation. In the DS/CDMA communication over the additive white Gaussian noise (AWGN) channel, the desired signal vector is merely the specific user's spreading sequence, which is also required to implement the matched correlator.

Unfortunately, the perfect knowledge of the desired signal vector is not available when there is a timing error in acquisition. This mismatch will cause the MOE algorithm to adjust the linear detector in a wrong direction, such that the resultant detector will cause signal degradation and noise enhancement [5, 6]. A constrained MOE (CMOE) algorithm [5, 6] has been presented to solve this problem by introducing a constraint on the norm of the tap-weight vector of the linear detector. Unfortunately, the Lagrange multiplier determining the constraint cannot be automatically decided to achieve a compromise between larger tolerance to mismatch and interference suppression capability. In [7], the author proposed an inverse filtering method based on the MOE approach for blind demodulation of DS/CDMA signals in the presence of multipath. Some additional constraints are made to reject other multipath components of the desired user in order to avoid the signal cancellation. However, the algorithm does not utilise the multipath diversity, which is commonly used to improve the performance of reception in the RAKE receiver.

In this paper, the effect of mismatch caused by the timing error on the MOE and Griffiths' algorithms is investigated and compared. To mitigate the effect of mismatch, we present a new blind adaptive algorithm for near–far resistant DS/CDMA demodulation in the presence of timing error. The proposed receiver consists of three parallel Griffiths' filters and the decision statistic is formed by linearly combining the output of the filters. In addition, the new algorithm can result in the estimation of the timing error adaptively, which can be useful for the tracking loop. The convergence speed of the Griffiths' algorithm can be accelerated using a variable step-size scheme [9]. Thus, the new blind algorithm is useful in practice. In [10, 11], authors developed the methods of near–far resistant estimation for the code timing. The emphasis of our paper, however, is the effect of the timing error on the near–far resistant demodulation.

2 Theoretical background

2.1 Asynchronous DS/CDMA

In a DS/CDMA communication environment with K active users, the kth user transmits the antipodal

IEE Proceedings online no. 19990284

DOI: 10.1049/ip-com:19990284

Paper first received 27th November 1997 and in revised form 19th October 1998

The authors are with the Department of Electronics Engineering and Center for Telecommunications Research, National Chiao Tung University, Hsin-Chu, Tawian 300, Republic of China

symbol $b_k[j] \in \{-1, +1\}$ with amplitude A_k as follows:

$$r_k(t) = \sum_{j=-\infty}^{\infty} A_k b_k[j] s_k(t - jT_b - \tau_k) \cos(\omega_c t + \theta_k) \quad (1)$$

where ω_c is the carrier frequency, T_b is the symbol interval, τ_k is the time delay and θ_k is the carrier phase relative to the receiver. To share the same frequency spectrum, each user is assigned with a unique spreading waveform given by:

$$s_k(t) = \sum_{n=0}^{N-1} a_k[n]\Pi(t - nT_c) \quad (2)$$

where $a_k[n] \in \{+1, -1\}$ is the nth element of the spreading sequence for the kth user and the chip waveform $\Pi(t)$ is usually a rectangular waveform of unit-amplitude and duration T_c. In general, T_c is assumed to be T_b/N and N is the processing gain. The received signal is then of the form $r(t) = \Sigma_{k=1}^{K} r_k(t) + x(t)$ where $x(t)$ is AWGN.

If the double frequency terms are ignored, the equivalent baseband sample at the output of the chip-matched filter can be expressed as:

$$r[m] = \sum_{k=1}^{K} \int_{mT_c}^{(m+1)T_c} r_k(t) \cdot 2\cos(\omega_c t)dt + x[m] \quad (3)$$

where $x[m]$ is the noise sample. Since $\tau_k \in [0, T_b)$, the delay relative to the receiver can be written as $\tau_k = (n_k + \delta_k)T_c$, where $0 \le n_k \le N - 1$ is an integer and $\delta_k \in [0, 1)$. The samples within one observation interval of length T_b, $[r[jN], ..., r[(j + 1)N - 1]]$, can thus be expressed as a vector:

$$\mathbf{r}(j) = \sum_{k=1}^{K} b_k[j-1]\mathbf{v}_k^{-1} + b_k[j]\mathbf{v}_k^{0} + \mathbf{x}(j) \quad (4)$$

where

$$\mathbf{v}_k^{-1} = A_k \left\{(1-\delta_k)T_L^{N-n_k}\mathbf{a}_k + \delta_k T_L^{N-n_k-1}\mathbf{a}_k\right\}$$
$$\mathbf{v}_k^{0} = A_k \left\{(1-\delta_k)T_R^{n_k}\mathbf{a}_k + \delta_k T_R^{n_k+1}\mathbf{a}_k\right\}$$

and $\mathbf{a}_k = [a_k[0], a_k[1], ..., a_k[N-1]]^T$. In the above expression, $\mathbf{x}(j)$ is the AWGN vector and the terms $\cos(\theta_k)$ are absorbed into A_k. Note that T_L^n and T_R^n are the acyclic n-shift operators, which shift the elements of a vector to left and right acyclically, respectively.

2.2 Equivalent channel model

Taking the first user to be the desired transmission (therefore, $\tau_1 = \theta_1 = 0$), it is convenient to describe the asynchronous DS/CDMA channel by the following equivalent synchronous model as follows:

$$\mathbf{r}(j) = b_1[j]A_1\mathbf{u}_1 + \sum_{l=2}^{L} b_l[j]A_l\mathbf{u}_l + \mathbf{x}(j) \quad (5)$$

where $b_1[j]$ is the desired symbol modulated by the desired signal vector $\mathbf{u}_1$, and $b_l[j]$, for $2 \le l \le L$, are interfering symbols due to intersymbol interference and multiple-access interference and $\mathbf{u}_l$ are the interference vectors modulating these symbols with amplitude A_l. Note that, when $\tau_1 = 0$, the desired signal vector is equal to the spreading sequence of the desired user, that is, $\mathbf{u}_1 = \mathbf{a}_1$.

For this equivalent channel, the signal-to-noise ratio (SNR) is defined as SNR $= A_1^2\|\mathbf{u}_1\|^2/\sigma^2$, where σ^2 is the variance of AWGN samples. Since $\|\mathbf{u}_1\|^2$ depends on the delay τ_1, for simplicity, we define the SNR to be the one corresponding to a symbol- and chip-synchronous system. That is, SNR $= NA_1^2/\sigma^2$. Throughout all experiments in the subsequent Sections, each interfering user is assumed to have equal power and the near–far ratio (NFR) denotes the ratio of the power of each interfering user to the power of the desired user.

The MMSE linear detector demodulates the transmitted symbol of interest as $\hat{b}_1[j] = \text{sgn}(\mathbf{w}^T\mathbf{r}(j))$, where the FIR filter $\mathbf{w}$ minimises the mean-squared error [3, 4] (MSE) between the desired symbol and the test statistic as follows $J = E\{(b_1[j] - \mathbf{w}^T\mathbf{r}(j))^2\}$. Since the bits $b_l[j]$ are uncorrelated, the optimum tap-weight vector is given by

$$\mathbf{w}_o = \mathbf{R}^{-1}\mathbf{p} \quad (6)$$

where $\mathbf{R} = E\{\mathbf{r}(j)\mathbf{r}^T(j)\}$ and $\mathbf{p} = E\{b_1[j]\mathbf{r}(j)\} = A_1\mathbf{u}_1$ are the correlation matrix of the received signal vectors and the cross-correlation between the desired symbol and the received signal vector, respectively. When the interference is stationary, the correlation matrix $\mathbf{R}$ is positive definite and nonsingular, and the optimum tap-weight vector is unique.

2.3 Blind adaptation algorithms

The MOE and Griffiths' algorithms are the commonly used blind adaptation algorithms for near–far resistant demodulation. Their adaptation equations are described briefly below.

The MOE algorithm [5, 6] decomposes the impulse response of a linear detector into the sum of two orthogonal components: $\mathbf{w} = \mathbf{u}_1 + \mathbf{v}$, in which $\mathbf{u}_1$ is the matched filter corresponding to the desired user and $\mathbf{v}$ is an adaptive filter. The linear detector intends to minimise the mean output energy:

$$MOE(\mathbf{v}) = E\left\{(\mathbf{w}^T\mathbf{r}(j))^2\right\} \quad (7)$$

subject to $\mathbf{u}_1^T\mathbf{v} = 0$. Due to this constraint, the output energy due to the desired user is transparent to the choice of $\mathbf{v}$, and the resultant detector is expected to suppress the interference while preserving the desired signal. To satisfy the constraint $\mathbf{u}_1^T\mathbf{v} = 0$, the stochastic gradient-descent adaptation rule must find the projection of the gradient of the output energy on the linear subspace that is orthogonal to $\mathbf{u}_1$. The adaptation equation is thus given by:

$$\mathbf{v}(j+1) = \mathbf{v}(j) - \mu z(j)[\mathbf{r}(j) - z_{MF}(j)\mathbf{u}_1] \quad (8)$$

where μ is the step size, $z(j) = \mathbf{w}(j)^T\mathbf{r}(j)$ is the output of the MOE receiver and $z_{MF}(j) = \mathbf{u}_1^T\mathbf{r}(j)$ is the output of the matched correlator.

The Griffiths' algorithm [8, 13] is an approximate implementation of the method of steepest descent like the least mean-squared (LMS) algorithm [14]. Utilising the property of $\mathbf{p} = A_1\mathbf{u}_1$ and replacing the correlation matrix $\mathbf{R}$ with the instantaneous estimate $\mathbf{r}(j)\mathbf{r}^T(j)$ yield the adaptation equation given by:

$$\mathbf{w}(j+1) = \mathbf{w}(j) + \mu[\mathbf{u}_1 - z(j)\mathbf{r}(j)] \quad (9)$$

where μ is the step size and $z(j) = \mathbf{w}^T(j)\mathbf{r}(j)$ is the output of the detector. If the step size is sufficiently small [12], the Griffiths' algorithm will make the adaptive detector converge to $\mathbf{w}_s = \mathbf{R}^{-1}\mathbf{u}_1$, which is a scaled MMSE solution. The scaling will not affect the binary decision of the transmitted symbol so the amplitude A_1 is not required to be estimated during the adaptation.

3 Mismatch

We assumed in Section 2 that the desired signal vector is merely the spreading sequence of interest. This may not be true when there is a timing error in acquisition. The relationship between the timing error and the desired signal vector can be illustrated in Fig. 1. When the clock of the receiver leads that of the transmitted symbols by $\delta_1 T_c$ $(0 \leq \delta_1 \leq 1)$, the desired signal vector can be expressed by:

$$\mathbf{u}_1 = (1-\delta_1)\mathbf{a}_1 + \delta_1 T_R^1 \mathbf{a}_1 \qquad (10)$$

Alternatively, when the clock of the receiver lags behind by $\delta_1 T_c$ $(0 \leq \delta_1 \leq 1)$, the desired signal vector can be expressed by:

$$\mathbf{u}_1 = (1-\delta_1)\mathbf{a}_1 + \delta_1 T_L^1 \mathbf{a}_1 \qquad (11)$$

The desired signal vector is thus a linear combining of the spreading sequence of interest and its shift version. If $\mathbf{a}_1$ is used as the nominal desired signal vector, the mismatch causes the performance loss to the blind algorithms.

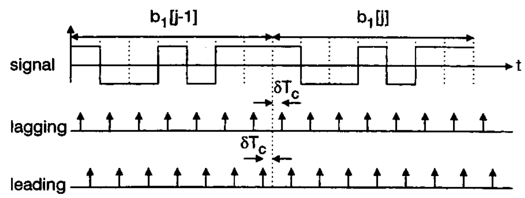

Fig. 1 *Relationship between desired signal vector and timing error*

The effect of mismatch on the MOE algorithm has been investigated in [5–7]. Since the adaptive filter $\mathbf{v}$ is no longer orthogonal to the exact desired signal vector, minimising the output energy will cancel the desired signal and the interference together. The continuous adaptation for the tap-weight vector will cancel the desired signal completely. The CMOE algorithm is one of the effective strategies for solving this problem. The constrained MOE solution is given by:

$$\mathbf{w}_C = (\mathbf{R} + \nu \mathbf{I})^{-1}\hat{\mathbf{u}}_1 \qquad (12)$$

where $\hat{\mathbf{u}}_1$ is the nominal desired signal vector and ν is the Lagrange multiplier for the constraint on $\|\mathbf{w}_C\|^2$.

Recall that, when the step size is sufficiently small [12], the Griffiths' algorithm will make the resultant detector converge to $\hat{\mathbf{w}}_G = \mathbf{R}^{-1}\hat{\mathbf{u}}_1$, where $\hat{\mathbf{u}}_1$ is the nominal desired signal vector. As long as the nominal desired signal vector is not orthogonal to the true one, the desired signal will not be cancelled completely. Consider two special cases: single-user case and very strong interference case. When only one user exists, the converged demodulator can be expressed by $\hat{\mathbf{w}}_G = (1/\sigma^2)(\hat{\mathbf{u}}_1 - \lambda \mathbf{u}_1)$ where $\lambda = \hat{\mathbf{u}}_1^T \mathbf{u}_1/((\sigma^2/A_1^2)+|\mathbf{u}_1|^2)$. The contribution of the desired user to the demodulator output is thus expressed as $A_1 \hat{\mathbf{w}}_G^T \mathbf{u}_1 = \lambda/A_1$, which is always positive and large as long as $\hat{\mathbf{u}}_1$ and $\mathbf{u}_1$ have highly positive correlation. When the interference level is very strong, the tap-weight vector of the converged demodulator is asymptotically orthogonal to the space spanned by the interference vectors [3]. The desired signal will not be cancelled if and only if the desired signal vector does not lie in the interference space.

The performance loss caused by the timing error in acquisition to the blind algorithms can be investigated by examining the signal-to-interference ratio (SIR). The SIR is the ratio of the desired signal power to the power sum of noise and MAI at the output of the filter $\mathbf{w}$. That is,

$$\mathrm{SIR} = \frac{A_1^2(\mathbf{w}^T\mathbf{u}_1)^2}{\sum_{l=2}^{L} A_l^2(\mathbf{w}^T\mathbf{u}_l)^2 + \sigma^2\|\mathbf{w}\|^2} \qquad (13)$$

Considering the leading case, the SIR values for the MMSE demodulator and the converged detectors via the CMOE and Griffiths' algorithms are shown in Fig. 2 as a function of the timing offset. The simulation parameters are $K = 8$, NFR = 10dB and SNR = 20dB. Each user is modulated by a unique Gold code sequence with code length $N = 15$, which is generated from a pair of polynomials $g_1(x) = 1 + x + x^4$ and $g_2(x) = 1 + x^3 + x^4$. As indicated from the plots, the timing error causes a significant performance loss to these blind algorithms, especially in the presence of large timing error. Consequently, a blind algorithm for near–far resistant demodulation is required, that also can mitigate the effect of timing error.

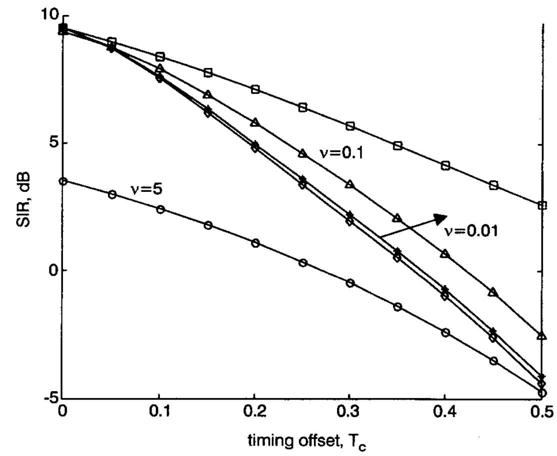

Fig. 2 *Effect of mismatch against timing error*
□——□ MMSE bound
◇——◇ Griffiths' algorithm
○——○ CMOE algorithm
△——△ CMOE algorithm
✳——✳ CMOE algorithm

4 Model-based Griffiths' algorithm

When the timing error is introduced, the desired signal vector can be expressed in the form of eqn. 10 or eqn. 11. Under the timing error the resultant MMSE demodulator is thus given by:

$$\mathbf{w}_o = A_1\{(1-\delta_1)\mathbf{w}_N + \delta_1 \mathbf{w}_R\} \qquad (14)$$

or:

$$\mathbf{w}_o = A_1\{(1-\delta_1)\mathbf{w}_N + \delta_1 \mathbf{w}_L\} \qquad (15)$$

where $\mathbf{w}_R = \mathbf{R}^{-1}T_R^1\mathbf{a}_1$, $\mathbf{w}_L = \mathbf{R}^{-1}T_L^1\mathbf{a}_1$ and $\mathbf{w}_N = \mathbf{R}^{-1}\mathbf{a}_1$. Following the structure of the MMSE demodulator, we propose a model-based Griffiths' algorithm (MBGA) demodulator, as illustrated in Fig. 3. The MBGA demodulator adopts three adaptive FIR filters in parallel, which are implemented by the Griffiths' algorithm using $T_R^1\mathbf{a}_1$, $T_L^1\mathbf{a}_1$, and $\mathbf{a}_1$, respectively, as the nominal desired signal vectors. If the step-size is sufficiently small [12], the three adaptive FIR filters will converge to $\mathbf{w}_R$, $\mathbf{w}_L$ and $\mathbf{w}_N$, respectively. Furthermore, if the timing error δ_1 can be estimated and whether the receiver clock leads or lags behind the timing of the desired user can be decided, the new algorithm can result in the demodulator by linearly combining $\mathbf{w}_R$ and $\mathbf{w}_N$ or $\mathbf{w}_L$ and $\mathbf{w}_N$.

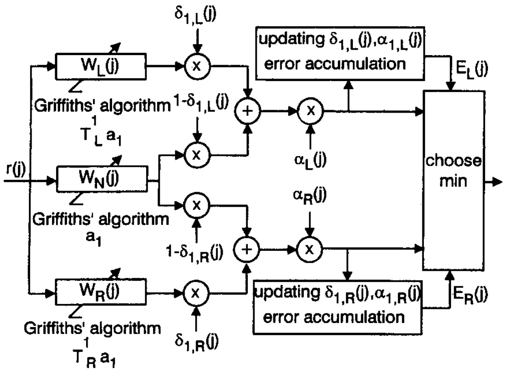

Fig.3 *Block diagram of model-based Griffiths' adaptation algorithm demodulator*

The timing error can be estimated recursively via the Godard algorithm, which minimises the cost function given by:

$$J_X(j) = E\Big\{\big[\alpha_X(j)|(1-\delta_{1,X}(j))z_N(j) + \delta_{1,X}(j)z_X(j)| - 1\big]^2\Big\}, \quad X = R, L \tag{16}$$

where $z_R(j)$, $z_N(j)$ and $z_L(j)$ are the output values of $\mathbf{w}_R(j)$, $\mathbf{w}_N(j)$ and $\mathbf{w}_L(j)$, respectively. Note that $\alpha_R(j)$ and $\alpha_L(j)$ are the gain factors corresponding to the leading and lagging cases, respectively. Whether the receiver clock leads or lags behind the timing of the desired user can be decided by comparing the accumulated decision errors during the adaptation process. Table 1 presents the summary of the new blind adaptive algorithm.

Table 1: Summary of the model-based Griffiths' adaptation algorithm

For each iteration, j = 1, 2, ..., compute

Griffiths' algorithm:

$\mathbf{w}_R(j+1) = \mathbf{w}_R(j) + \mu_1[T_R^1\mathbf{a}_1 - z_R(j)\mathbf{r}(j)]$, $z_R(j) = \mathbf{w}_R^T(j)\mathbf{r}(j)$

$\mathbf{w}_N(j+1) = \mathbf{w}_N(j) + \mu_1[\mathbf{a}_1 - z_N(j)\mathbf{r}(j)]$, $z_N(j) = \mathbf{w}_N^T(j)\mathbf{r}(j)$

$\mathbf{w}_L(j+1) = \mathbf{w}_L(j) + \mu_1[T_L^1\mathbf{a}_1 - z_L(j)\mathbf{r}(j)]$, $z_L(j) = \mathbf{w}_L^T(j)\mathbf{r}(j)$

Godard algorithm: $X = R, L$

$\alpha_X(j+1) = \alpha_X(j) - \mu_2 e_X(j)|y_X(j)|$

$\delta_{1,X}(j+1) = \delta_{1,X}(j) - \mu_2 e_X(j)\alpha_X(j)sign(y_X(j))[z_X(j) - z_N(j)]$

$e_X(j) = \alpha_X(j)|y_X(j)| - 1$

$y_X(j) = (1-\delta_{1,X}(j))z_N(j) + \delta_{1,X}(j)z_X(j)$

Error accumulation: $X = R, L$

$E_X(j+1) = (1-\beta)E_X(j) + \beta e_X^2(j)$

Combining:

if $E_R(j) < E_L(j)$ $\mathbf{w}(j) = (1-\delta_{1,R}(j))\mathbf{w}_N(j) + \delta_{1,R}(j)\mathbf{w}_R(j)$

else $\mathbf{w}(j) = (1-\delta_{1,L}(j))\mathbf{w}_N(j) + \delta_{1,L}(j)\mathbf{w}_L(j)$

5 Numerical results

In the following simulations the simulation parameters are N = 15, K = 8, NFR = 10dB and SNR = 20dB. The delay τ_1 of the desired transmission is selected for different simulation cases, while the delays τ_k, k = 2, ..., 8, are chosen randomly in [0, T_b) and then kept fixed. Table 2 shows the SIR values of the matched correlator, the MMSE demodulator and the inverse filtering demodulator [7] for different τ_1. The inverse filtering demodulator $\mathbf{w}$ is designed to minimise the mean output energy subject to $\mathbf{C}\mathbf{w} = \mathbf{f}$, where $\mathbf{C} = [T_L{}^1\mathbf{a}_1\ \mathbf{a}_1\ T_R{}^1\mathbf{a}_1]^T$ and $f = [0\ 1\ 0]^T$. The cosine of the angle between $\mathbf{u}_1$ and $\hat{\mathbf{u}}_1$, denoted by κ, is used to indicate how close the nominal desired signal vector is to the exact one.

Table 2: SIR of the matched correlator, the inverse filtering demodulator and the MMSE demodulator for different τ_1

τ_1/T_c	κ	$SIR_{matched}$ (dB)	SIR_{inv} (dB)	SIR_{mmse} (dB)
0.0	1.0000	0.80	11.44	15.86
0.15	0.9854	−1.73	10.00	13.57
0.30	0.9170	−4.44	8.25	10.66
0.40	0.7512	−6.58	6.04	7.23

The first experiment demonstrates the trajectory of the averaged SIR values against time when the perfect knowledge of the desired signal vector is acquired (that is, τ_1 = 0.0). The averaged SIR at the jth iteration is calculated by:

$$\mathrm{SIR}(j) = \frac{\sum_{r=1}^{M} A_1^2\left(\mathbf{w}_r^T(j)\mathbf{u}_1\right)^2}{\sum_{r=1}^{M}\left\{\mathbf{w}_r^T(j)\left[\mathbf{r}_r(j) - b_{1,r}[j]A_1\mathbf{u}_1\right]\right\}^2} \tag{17}$$

where the subscript 'r' denotes the particular run and the number of runs is M = 500. The plots in Figs. 4 and 5 show that both the MOE and the Griffiths' algorithms are expected to adapt the detector close to the MMSE solution under no mismatch.

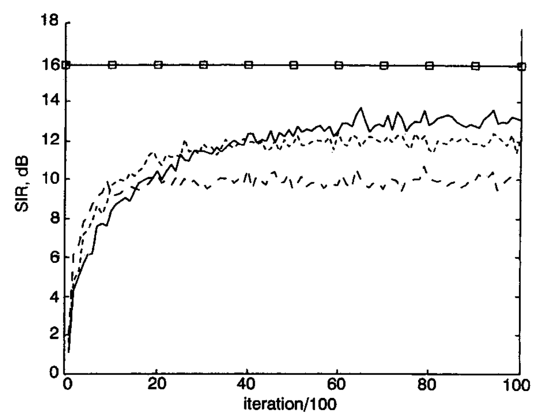

Fig.4 *Convergence of average SIR with perfect knowledge of desired signal vector for MOE algorithm*
□—□ MMSE bound
——— stepsize = 0.0008
- - - - stepsize = 0.0016
— — — stepsize = 0.0032

The second experiment demonstrates the convergence trajectory of the averaged SIR values against time under mismatch due to the imperfect timing synchronisation. The Lagrange multiplier used for the constrained MOE algorithm is v = 0.1. The plots in Figs. 6–8 show that the MOE algorithm fails to implement the demodulator in the presence of large timing error. The output SIR decreases to an unacceptable

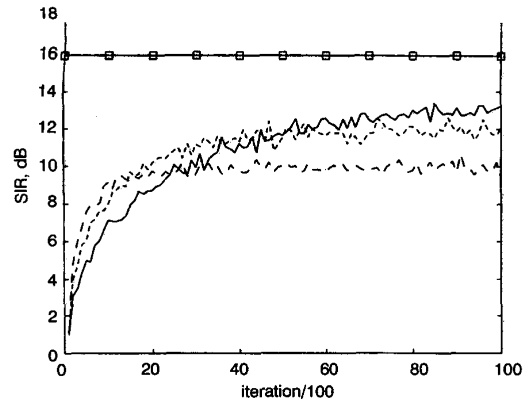

Fig. 5 *Convergence of average SIR with perfect knowledge of desired signal vector for Griffiths' algorithm*
□——□ MMSE bound
——— stepsize = 0.0008
- - - - stepsize = 0.0016
— - — stepsize = 0.0032

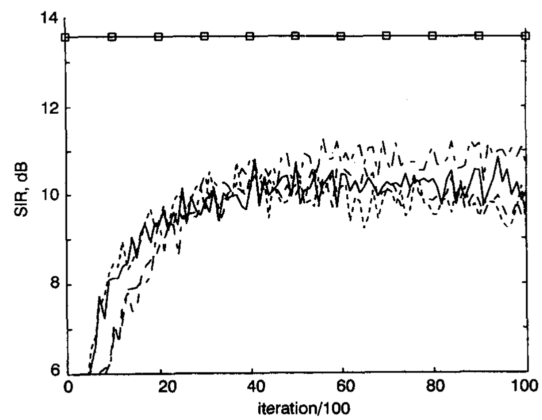

Fig. 6 *Convergence of average SIR for different blind algorithms in presence of mismatch for $\tau_l = 0.15T_c$*
□——□ MMSE bound
— - — MGBA
——— constrained MOE
— — — Griffiths'
- - - - MOE

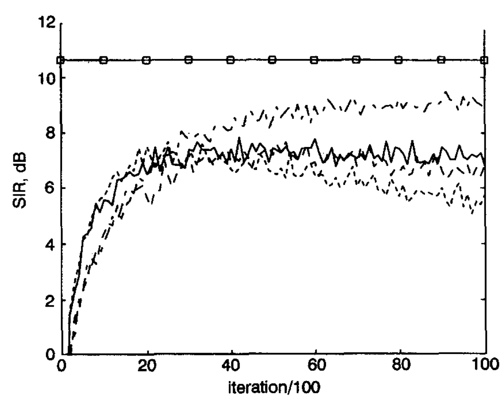

Fig. 7 *Convergence of average SIR for different blind algorithms in presence of mismatch for $\tau_l = 0.30T_c$*
□——□ MMSE bound
— - — MGBA
——— constrained MOE
— — — Griffiths'
- - - - MOE

level after a large number of iterations. The CMOE and the Griffiths' algorithms are robust against the effect of the mismatch in comparison with the MOE algorithm. However, their performance is worse relative to the MMSE bound. The MBGA demodulator can provide the significant improvement in output SIR over all other adaptation algorithms. Due to the misadjustment in adaptive implementation, there is some performance loss in the MBGA demodulator compared to the MMSE bound. However, the SIR of the MBGA is always larger than that of the inverse filtering demodulator. The trajectory of the estimated timing offset is shown in Fig. 9.

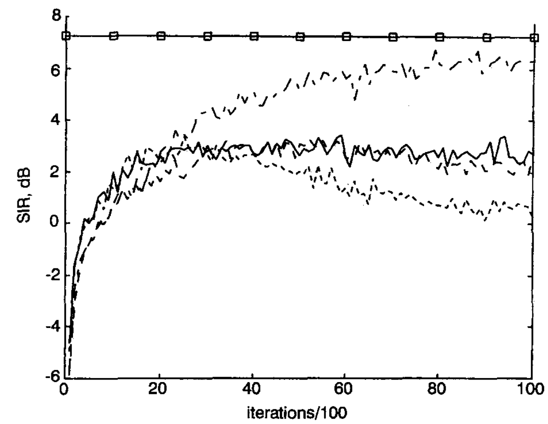

Fig. 8 *Convergence of average SIR for different blind algorithms in presence of mismatch for $\tau_l = 0.45T_c$*
□——□ MMSE bound
— - — MGBA
——— constrained MOE
— — — Griffiths'
- - - - MOE

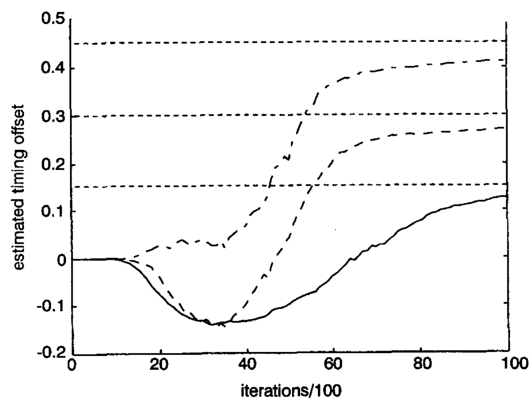

Fig. 9 *Trajectory of estimated timing offset by MBGA demodulator*
——— timing offset = $0.15T_c$
- - - - timing offset = $0.30T_c$
— - — timing offset = $0.45T_c$

6 Conclusion

In this paper, the performance of the MOE and the Griffiths' algorithms was investigated and compared. The CMOE and the Griffiths' algorithms are robust against the effect of mismatch in adaptation of the receiver, compared to the MOE algorithm. A new blind adaptive algorithm was proposed to mitigate the effect of mismatch caused by the timing error in synchronisation. The new algorithm can provide a significant improvement in the output SIR over the Griffiths' algorithm and modified MOE algorithms. The timing error is also estimated adaptively and the estimation can be used for further improving the accuracy in synchronisation.

7 Acknowledgment

This work is supported by the National Science Council of Republic of China under grant NSC-86-2221-E-009-053.

8 References

1 ZIEMER, R.E., and PETERSON, R.L.: 'Digital communications and spread spectrum systems' (Macmillan, New York, 1985)
2 PROAKIS, J.G.: 'Digital communications' (McGraw-Hill, New York, 1995, 3rd edn.)
3 MADHOW, U., and HONIG, M.L.: 'MMSE interference suppression for direct-sequence spread-spectrum CDMA', *IEEE Trans. Commun.*, 1994, **42**, (12), pp. 3178–3188
4 MILLER, S.L.: 'An adaptive direct-sequence code-division multiple-access receiver for multiuser interference rejection', *IEEE Trans. Commun.*, 1995, **43**, (2/3/4), pp. 1746–1755
5 HONIG, M.L., MADHOW, U., and VERDU, S.: 'Blind adaptive interference suppression for near–far resistant CDMA'. Proceedings of 1994 IEEE Globecom, Globecom'94, San Francisco, CA, 1994, pp. 379–384
6 HONIG, M.L., MADHOW, U., and VERDU, S.: 'Blind adaptive multiuser detection', *IEEE Trans. Inf. Theory*, 1995, **41**, (4), pp. 944–960
7 TSATSANIS, M.K.: 'Inverse filtering criteria for CDMA systems', *IEEE Trans. Signal Process.*, 1997, **45**, (1), pp. 102–112
8 ZECEVIC, N., and REED, J.H.: 'Blind adaptation algorithms for direct-sequence spread spectrum CDMA single-user detection'. Proceedings of 1997 IEEE *Vehicular technology* conference, VTC'97, Phoenix, AZ, USA, 1997, pp. 2133–2137
9 HWANG, H.C., and WEI, C.H.: 'Adaptive variable step-size Griffiths' algorithm for blind demodulation of DS/CDMA signals', *submitted to IEIEC Trans. Commun.*, 1998,
10 SMITH, R.F., and MILLER, S.L.: 'Code timing estimation in a near–far environment for direct-sequence code-division multiple-access'. Proceedings of 1994 IEEE Military Comm., Milcom'94, Fort Monmouth, NJ, USA, 1994, pp. 47–51
11 STROM, E.G., PARKVALL, S., MILLER, S.L., and OTTERSTEN, B.E.: 'Propagation delay estimation in asynchronous direct-sequence code-division multiple access systems', *IEEE Trans. Commun.*, 1996, **44**, (1), pp. 84–93
12 GRIFFITHS, L.J.: 'A simple adaptive algorithm for real-time processing in antenna arrays', *Proc. IEEE*, 1969, **57**, (10), pp. 1696–1704
13 TREICHLER, J.R., JOHNSON, C.R., and LARIMORE, Jr. M.G.: 'Theory and design of adaptive filters' (John Wiley & Sons, New York, 1987)
14 HAYKIN, S.: 'Adaptive filter theory' (Prentice-Hall, N.J., 1991, 2nd edn.)