MSE and BER Performances of LMMN Receiver in DS-CDMA Over Frequency-Selective Slow Rayleigh Fading Channels

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***Abstract* - This paper investigates the performance of using the Least-Mean- Mixed-Norm algorithm (LMMN) in the adaptation of asynchronous DS-CDMA slow fading, non-linear receiver. The investigations study the effect of using various mixing parameter (λ) and step-size (μ) on the performance of the proposed algorithm in terms of mean-square error (MSE) and bit-error-rate (BER). Computer simulation results indicate that LMMN with lamda (λ) equals 0.9 and step-size (μ) equals $5x10^{-3}$ give the best performance. Moreover it is demonstrated that non-linear receivers adapted by the proposed algorithm have faster convergence rate and similar BER performance, in comparison with the NLMS adaptive receiver.**

***Index Terms* - Adaptive algorithms, DS-CDMA, Slow fading, Mobile communications, ,**

I. INTRODUCTION

Various adaptive MMSE receivers have been proposed for the detection of DS-CDMA systems. For AWGN channels, adaptive MMSE receivers were developed based on the standard quadratic cost function [1], [2]. The linear and non-linear MMSE detectors considered in [3] are single-user detectors in the sense that they demodulate the bit stream of one user at a time.

For high speed phase coherent communications as required in 3G mobile systems, it is shown in [4] that the adaptive MMSE detector is not able to track the phase of the incoming signal especially when the received signal experiences a deep fade. On the other hand, the proposed receiver in [3] performs optimal phase tracking and channel equalization jointly.

So far, the Normalized-Least-Mean-Square (LMS) algorithm has proved popular for many applications because of its simplicity and ease of implementation. However, many alternatives can also be defined to improve the adaptation performance in specific statistical environments [5-9]. Hence the proposed receiver in this paper is based on using the least mean mixed-norm algorithm in [8] to update the tap coefficients of the feedforward and feedback filters.

A second-order digital phase-locked loop (DPLL) is used here to track the phase of the incoming signal. Also recently two papers [10,11] have been published that investigate the performance of the LMMN algorithm but in a fast fading environment. The results were in support of the results obtained in this paper. Moreover, in this paper extensive simulation tests, to examine and determine the best values of the proposed algorithm's mixed parameter and step size, have been carried out.

II. SYSTEM MODEL

In this work, asynchronous DS-CDMA system with K active users has been considered. QPSK with symbol duration T_s is assumed while the chips of the spreading sequence have duration T_c. The unit-energy signature waveform of the k^{th} user is given by:

$$s_k(t) = \frac{1}{\sqrt{T_s}} \sum_{j=1}^{N} \delta_k[j]\Psi(t-(j-1)T_c) \tag{1}$$

Where $\delta_k[n] \in \{-1,+1\}$ is the n^{th} chip of the k^{th} user and $N=T_s/T_c$ is the processing gain of the system. The chip waveform $\Psi(t)$ is zero for $t \notin (0,T_c)$. Each user's transmitted signal is assumed to pass through a frequency-selective slow Rayleigh-fading channel. AWGN is considered here. The DS-CDMA system model used in this paper is shown in Fig. 1.

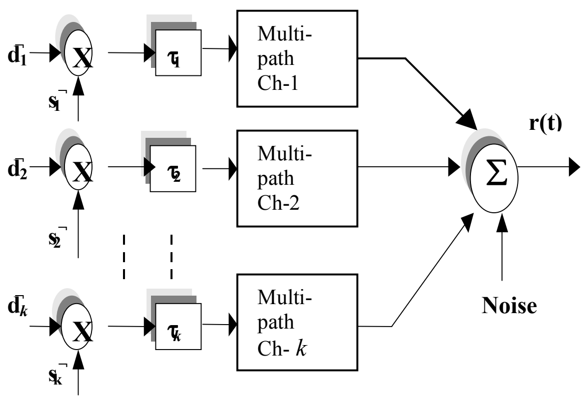

Fig. 1 K users DS-CDMA System

The received signal from K users is given in equation 2.

$$r(t)=\sum_{k=1}^{K} r_k(t)+n(t) \tag{2}$$

where $r_k(t)$ is represented as

$$r_k(t)=\sum_{i=-\infty}^{\infty} d_k[i]\sum_{l=1}^{L} c_k[l]s_k(t-iT_s-t_k[l]) \tag{3}$$

$d_k[i]=a_k[i]+jb_k[i]$ is the i[th] QPSK symbol of the k[th] user, and $a_k[i],b_k[i]\in\{-1,+1\}$, L is the number of paths of user k, the complex quantity $c_k[\ell]$ is the amplitude and phase variation of the ℓ^{th} path of user k and $t_k[\ell]$ is the reception time of the ℓ^{th} path of user k.

The amplitude and phase of the $c_k(\ell)$ in equation (3) are Rayleigh and uniformly distributed, respectively. The delay of each user is defined by the arrival time of the first ray of that user, $t_k[\ell]$ where $t_k[\ell]\in[0,T_s)$.

III. RECEIVER STRUCTURE

The proposed receiver model is shown in Fig. 2. Joint operation of equalization and phase tracking is considered here. Assuming perfect estimation of the transmission time of each user, the signal to the input of the k[th] user chip-match filter (CMF) is delayed by T_s-τ_k, and then sampled at $\Delta=T_c$. Without loss of generality, the user of interest is assumed as user number 1.

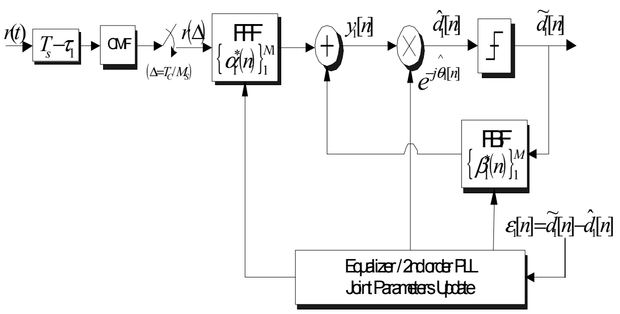

Fig.2 Receiver's structure

The N taps of the FFF are arranged in a row vector α_l^T , and the input signal samples currently stored in the FFF are given by:

$$r_1(n)=[r(nT_s+T_c+\tau_1),....,r(nT_s+NT_c+\tau_1)]^T \tag{4}$$

The FBF has tap weights β_1^T and operates on *M* previous detected symbols.

$$d_1(n)=\left[d_1^{\wedge}[n-1],.....,d_1^{\wedge}[n-M]\right]^T \tag{5}$$

If we define the coefficients vector u_1 and data vector x_1 as:

$\mathbf{u}_1\equiv[\alpha_1^T, \beta_1^T]^T$, $\mathbf{x}_1[n]\equiv[r1^T, d_1^T]^T$ (6)

then the soft-symbol estimate of the n[th] QPSK symbol of the 1[st] user is $d^{\wedge}_1[n] = u_1.x_1[n]\, e^{-j\theta^{\wedge}1[n]}$ which in turn will be fed to the hard symbol decision to produce:

$$d_1^{\wedge}[n]=\operatorname{sgn}\left[\operatorname{Re}\{d_1^{\wedge}[n]\}\right]+j\operatorname{sgn}\left[\operatorname{Im}\{d_1^{\wedge}[n]\}\right] \tag{7}$$

In decision-directed mode, $d_1[n]$ should be substituted by $d_1^{\sim}[n]$. Due to the time varying nature of the channel response, optimal values of the receiver parameters are also time varying. Therefore, the equalizer must be designed to adaptively compensate for time variations in the channel characteristics. The NLMS adaptive algorithm, based on $J(n)=E\{\varepsilon^2(n)\}$, is used to updates the equalizer as follows [3]:

$$u_1[n+1]=u_1[n]+\frac{\mu_{NLMS}}{\|x_1[n]\|^2+\gamma}x_1[n]\varepsilon_1^*[n]e^{-j\theta_1^{\wedge}[n]} \tag{8}$$

μ_{NLMS} is the NLMS step-size and γ is a small positive constant used to ensure stability if the input signal power is low.

IV. LMMN ALGORITHM

The proposed LMMN adaptive algorithm, based on:

$$J(n)=\lambda E\{\varepsilon^2(n)\}+(1-\lambda)E\{\varepsilon^4(n)\}, \tag{9}$$

is used to update the equalizer as in Eqn. (10). $\lambda\in[0, 1]$ is the mixing parameter. When $\lambda = 1$, Eqn. (9) becomes the error norm for the LMS algorithm, whereas when $\lambda = 0$, Eqn. (9) becomes the error norm for the LMF algorithm. Judicious choice of λ thereby provides an algorithm with intermediate performance between that of the LMS and LMF, and a mechanism to mitigate the problem of instability within the LMF algorithm. Moreover, for operation in a statistically nonstationary environment, the mixing parameter may be adapted to match appropriately the properties of measured signals.

The LMMN adaptive algorithm, based on J(n) given in Eqn. (9), is used to updates the equalizer as follows [8]:

$$u_1[n+1]=u_1[n]+\mu_{LMMN}\,\hat{\nabla}_{\alpha_1(n)}\,J(n) \tag{10}$$

where μ_{LMMN} is the LMMN algorithm adaptation gain and $\hat{\nabla}_{\alpha_1(n)}\,J(n)$ is the instantaneous estimate of the gradient of the error norm J(n) evaluated at the current value of the weight vector $u_1(n)$. Differentiation of Eqn. (10) with respect to $u_1(n)$ yields the LMMN update equation and as follows:

$$u_1[n+1]=u_1[n]+2\mu_{LMMN}\varepsilon(n)(\lambda+2(1-\lambda)\varepsilon^2(n)r_1(n) \tag{11}$$

Also [3],

$$\theta_1[n+1]=\theta_1[n]+K_1\phi_1[n]+K_2\sum_{i=0}^{n}\phi_1[n] \tag{12}$$

$$\phi_1[n]=\mathrm{Im}\left\{\hat{d}_1[n]\,\tilde{d}_1^{*}[n]\right\} \tag{13}$$

where $\varphi_1[n]$ is the phase detector output, $K_1>>K_2$ are proportional and integral tracking constants, It should be noted that the structure shown in Fig. 2 is applicable to all other users.

V. RESULTS and DISCUSSION

The proposed receiver is tested by means of computer simulations in an asynchronous system where the arrival time of the first ray of each user satisfies $\tau_k[1]\sim U(0,N)$. 31-chip Gold sequences are used and the modulation scheme is QPSK.

The multipath channel considered here is Rayleigh multipath frequency selective slow fading implies that $T_m > T_s$, the delay time is greater than the symbol time. The channel is slow fading with a Doppler frequency of 45 Hz.

In this paper it is assumed that we have 5 equal power users. All the performances shown in Figs. 3-10 are obtained using the channel specified as follows: The first path is delayed by 0.0 μsec (0 chips) with an amplitude of 0.7, the second path is delayed by 1.5 μsec (46 chips) with an amplitude of 0.5, and the third path is delayed by 1.875 μsec (58 chips) with an amplitude of 0.332.

Firstly, we demonstrate in Fig. 3 the MSE performance of the proposed algorithm for different values of lamda (λ).

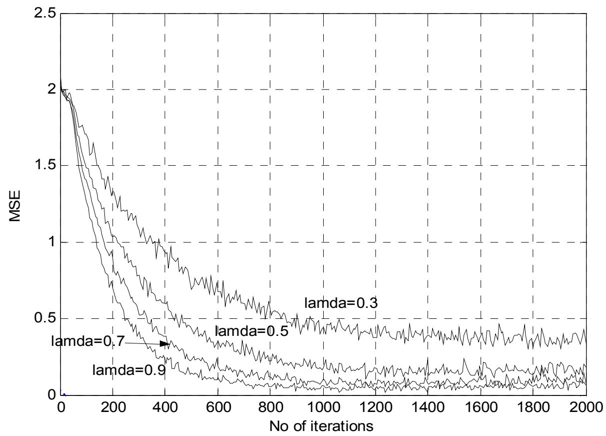

Fig. 3 Learning curves of the LMMN (μ=3e-5) for various lamda (λ)

Several values of λ were tested (0.3, 0.5, 0.7, and 0.9) and it is clearly demonstrated that the LMMN algorithm with λ=0.9 achieves the fastest convergence. Also the MSE performance for λ equals 1.0 has been tested and it is similar to the performance of λ equals 0.9. In Fig. 4 the BER performance of the proposed receiver, for various λ, is examined too.

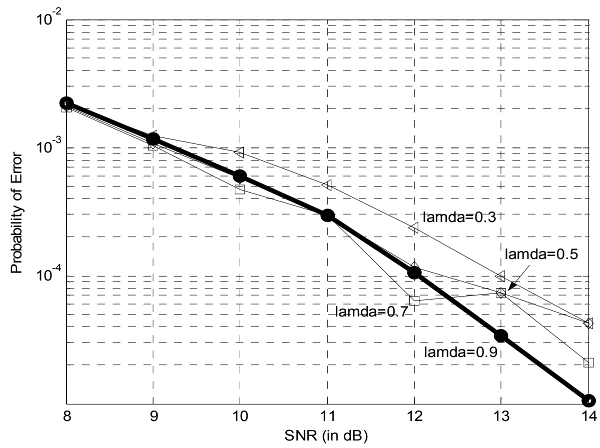

Fig. 4 BER performance of the LMMN (μ=3e-5) for various lamda (λ)

It can be observed that the BER performance of the proposed receiver adapted by the LMMN algorithm with λ=0.9 achieve the best performance. Note that, in both figures, the value of μ_{LMMN} equals $3\text{x}10^{-5}$. Moreover extensive tests have been carried out to examine the performance of the proposed algorithm using powers of 1.0 > λ >0.9. These tests revealed that λ=0.9 gives better performance in both MSE and BER. However, the detailed results of this investigation have been omitted here due to space limitations. To determine the best step-size of the proposed algorithm, Figs. 5&6 show the MSE and BER performances, respectively of the LMMN adaptive receiver, $\lambda= 0.9$, for various step-sizes.

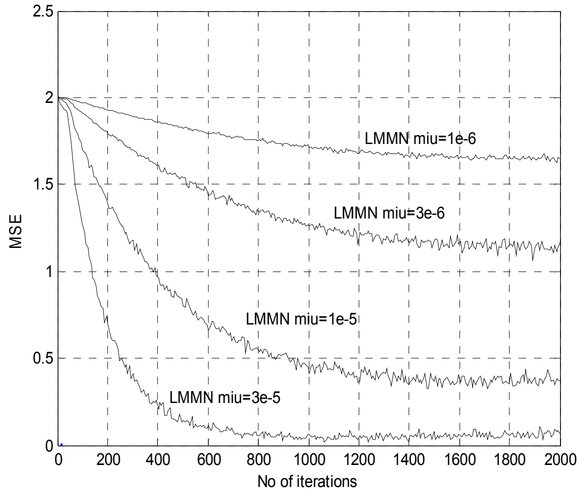

Fig. 5 Learning curves of the LMMN (λ =0.9) for various step-sizes

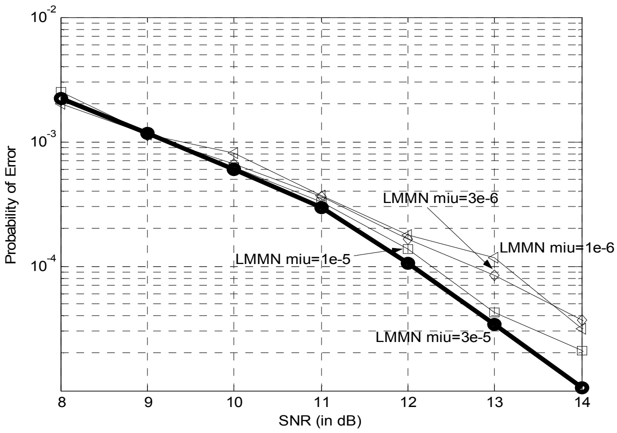

Fig. 6 BER performance of the LMMN (λ =0.9) for various step-sizes

It is clear that the LMMN performance with $\mu_{LMMN} = 3x10^{-5}$ performs better which confirms the earlier observation. The best performance is chosen based on the compromise between the stability in the MSE performance and low bit error rate in the BER performance**.**

To compare the performance of the proposed algorithm with the traditional NLMS algorithm, the MSE and BER performances of the NLMS, for various values of step-sizes, are plotted in Figs. 7 and 8.

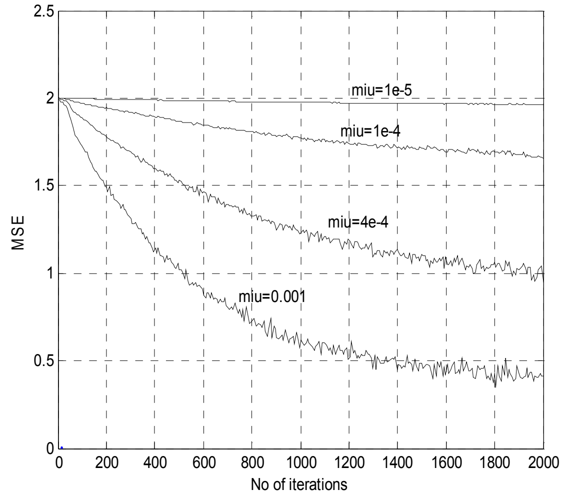

Fig. 7 Learning curves of the NLMS algorithm for various step-sizes

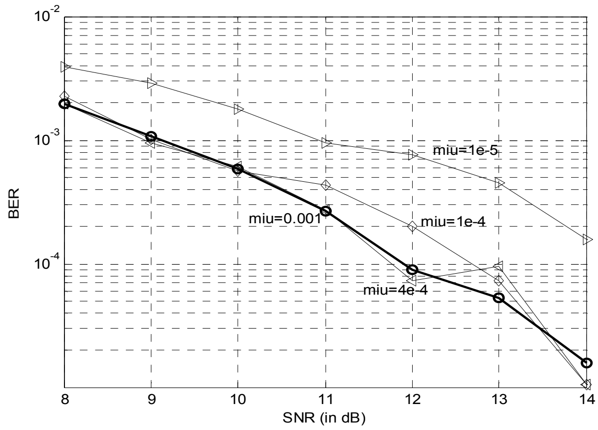

Fig. 8 BER performance of the NLMS algorithm for various step-sizes

To highlight the advantage of using the LMMN algorithm in updating the tap weights of both the FFF and the FBF compared to the NLMS algorithm, the MSE and BER performances of the two algorithms are plotted, respectively, in Figs. 9 and 10. Simulations results plotted in Fig. 9 show that using the proposed algorithm exhibits faster convergence compared with the traditional NLMS.

The BER plots in Fig. 10 show that the proposed algorithm's performance is similar to that of the NLMS algorithm and it is slightly better at high SNR.

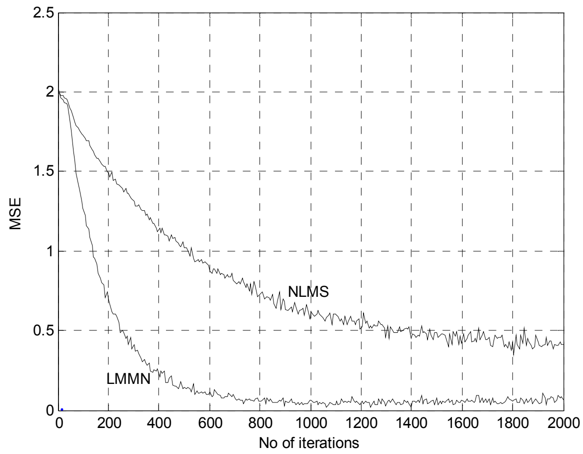

Fig. 9 Learning curves of the proposed algorithm (LMMN) and the NLMS algorithm

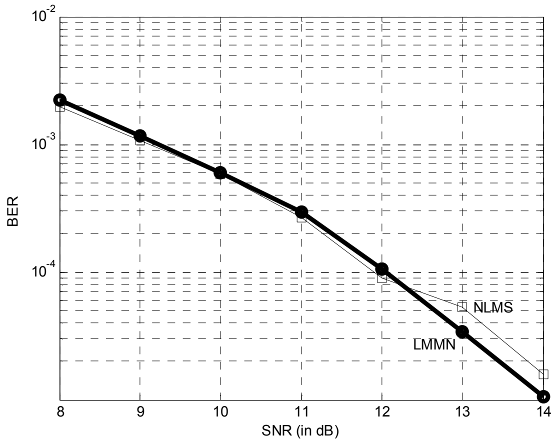

Fig. 10 BER performance of the proposed algorithm (LMMN) and the NLMS algorithm

In both Figs. 9 and 10, the step-size used for the NLMS algorithm is 0.001 and for the LMMN algorithm it is $3x10^{-5}$.

The next step in this research is to use the variable step size NLMS [9] in the adaptation process of the DS-CDMA receiver's structure.

VI. CONCLUSION

The use of the least mean mixed-norm adaptive algorithm, as an alternative to the NLMS algorithm, in Rayleigh slow fading DS-CDMA system has been investigated. Extensive computer simulation tests show that the best performance of the proposed algorithm is obtained when λ equals 0.9 and μ is $3x10^{-5}$. The proposed receiver structure using LMMN adaptive algorithm provides a fastest convergence, and similar BER performance compared to the NLMS adaptive algorithm, albeit at similar computational complexity.

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