Wireless communications has seen enormous growth over the last one and a half decades, and research into third (3G) and future generation communication systems continues unabated. Wide-band direct sequence code division multiple access (W-CDMA) is one of the leading candidates for the air interface standard due to its inherent multipath resistance and spectral efficiency. It is important to note that CDMA is not resource limited (like FDMA or TDMA), but its capacity is limited by the amount of multiple access interference (MAI).

DS-CDMA has the potential to have greatly enhanced performance over traditional 2G schemes, when coupled with advanced signal processing techniques at the physical layer. Examples of such techniques include multiuser detection (MUD) [1], smart antennas [2], space-time processing [3], and space-time multiuser detection [4]. MUD improves the performance of CDMA communication systems by reducing the amount of MAI in the desired user’s received signal. The MUD considered in this paper is categorised as a linear scheme and is applicable when short spreading codes are used.

Current trends in research [5], [6], [7], point towards the use of blind adaptive implementations of MUD schemes. Adaptive schemes are desirable since the communications channel is time varying (in terms of the number of users and fade values). This would require an ever changing MUD solution, which would be difficult and computationally very expensive to compute in real time, hence adaptive schemes are more practical. Traditionally, adaptive schemes make use of some a priori information at the receiver to adapt the MUD, e.g. a pilot channel or training sequence. These schemes are wasteful of radio resources, and therefore it is desirable to adapt the MUD blindly, i.e. without any pilot channel or training sequence, to increase the spectral efficiency. With blind schemes, the only knowledge the receiver has of the system is the timing and spreading code information of the desired user. Blind schemes are also desirable since a large portion of the MAI may be extra cellular, and thus the spreading codes of those users are not known at the receiver. Under these conditions non-blind techniques would be ineffective, and blind MUD would be the only technique possible.

The first blind adaptive scheme was proposed in [8], where a linear filter was adapted such that the output energy of the MUD was minimised, subject to a constraint. This was the constrained minimum output energy receiver (CMOE). The constraint was the spreading code of the desired user, and it prevented the receiver cancelling out the desired user’s signal. It was shown in [8] that the CMOE detector converges to the MMSE solution. The CMOE suffers from very poor performance under mismatch conditions when there is a high signal to noise ratio (SNR). Mismatch in this context refers to the discrepancy between the signature waveform expected at the receiver and that which actually arrives. Mismatch occurs due to the desired user’s signal propagating through an imperfect channel.

The constant modulus algorithm (CMA, or Godard Algorithm) [9] has been proposed as an alternative blind adaptive technique for MUD. The CMA makes use of the finite alphabet of digital signals and attempts to restore the desired signal to a constant modulus (amplitude with phase). In a multiuser CDMA system, there would be numerous constant modulus signals (corresponding to the users), and thus the conventional CMA cannot guarantee that the desired user is extracted. To this end two main derivatives of CMA have been proposed: linearly constrained (LC) CMA [10], and multiuser (MU) CMA [11]. MUCMA is computationally very expensive as it requires that all the constant modulus signals be extracted, and will not be considered in this paper. The LCCMA technique uses its estimate of the desired user’s signature sequence to prevent capture of unwanted users, and this is reason why LCCMA outperforms CMOE under mismatch conditions. It was shown in [12] that LCCMA has a unique solution and that it converges very closely to the MMSE solution. In [13], it was shown that under mismatch conditions the LCCMA technique has similar performance to the MMSE solution, and that it greatly outperforms the CMOE technique.

This paper discusses some of the performance issues associated with blind adaptive MUD using the LCCMA to adapt the filter coefficients. Excess MSE in the steady state arises due to adaptation with a non-zero step size. To date, a full analysis of the excess MSE with additive noise has not been analysed for CMA [14]. This paper investigates, through computer simulation, the effects of step size on BER and convergence rate. It was shown in [15], that if the amplitude of the desired user is incorrectly estimated, the convergence of the LCCMA algorithm is compromised. This phenomenon’s impact on BER has so far not been investigated in the literature, but is investigated via simulation in this paper.
The paper organised as follows: section I describes the system model and the adaptive receiver architecture. Section III illustrates the LCCMA algorithm and section IV presents simulation results. Concluding remarks are made in section V.

II. SYSTEM MODEL

A. Transmitter

A synchronous (wideband) DS-CDMA transmitter model for the uplink of a mobile radio network is considered. The baseband representation of the $k$th user’s transmitted signal is given by

$$x_k(t) = A_k \sum_{i=-\infty}^{\infty} b_k(i)s_k(t-iT)$$  \hspace{1cm} (1)

where $A_k$ and $s_k$ denote the amplitude and normalised spreading waveform of the $k$th user respectively, and $T$ is the data symbol duration. The $k$th user’s $i$th transmitted symbol $b_k(i)$ takes on the values $\{+1,-1\}$ with equal probability.

The spreading waveform takes the form

$$s_k(t) = \sum_{n=0}^{N-1} c_k(n)\psi(t-nT_c), \hspace{0.5cm} 0 \leq t \leq T_c$$  \hspace{1cm} (2)

where $N$ is the processing gain and $c_k$ is the $k$th user’s spreading code, $\psi(t)$ is the chip pulse shape, and the chip duration is defined as $T_c$. Note that $s_k(t)$ only takes on values in the interval $[0, T_c]$.

B. Channel

The signal is transmitted through a Rayleigh fading channel. There is no frequency selectivity.

C. Receiver

The signal received at the base station is given by

$$\hat{r} = \sum_{k=1}^{K} g_k b_k s_k + n$$  \hspace{1cm} (3)

where $g_k$ is the complex Rayleigh fade value of user $k$ and $n$ is the additive white Gaussian noise term with variance $\sigma^2$.

This signal is passed through a chip-matched filter and sampled at the chip-rate. These samples are concatenated into a length $N$ vector of received samples:

$$r_k(i) = [r_{k,0}(i) \quad r_{k,1}(i) \quad \ldots \quad r_{k,N}(i)]^T$$  \hspace{1cm} (4)

This vector is filtered by a finite impulse response (FIR) filter structure, as illustrated in figure 1. The output of the receiver is then the hard decision on the output of this filter, given by

$$\hat{b} = \text{sgn}(w^hr)$$  \hspace{1cm} (5)

where $w$ is the vector of filter coefficients.

III. LINEARLY CONSTRAINED CMA

The filter coefficients are chosen such that they minimise the fluctuations of the envelope of the filter’s output, away from a constant modulus. The CMA cost function that expresses this variation is

$$J_C = E\left(\left|\left(w^hr\right)^2 - R_2\right|\right)^2$$  \hspace{1cm} (6)

$$R_2 = E\left|s_k(n)\right|^4$$  \hspace{1cm} (7)

where $R_2$ is known as the dispersion factor.

The LCCMA technique (as the name suggests) minimises $J_C$ subject to a linear constraint. In this application of the LCCMA, the linear constraint is

$$w^hs = 1$$  \hspace{1cm} (8)

where the desired users is user 1. This constraint ensures that the desired user’s signal is captured and not one of the other transmitting users in the system.

The above constrained optimization problem, as it stands, is not amenable to conventional stochastic gradient techniques. The technique used in this paper to solve the above problem follows the methods used in [10] and [13], which are similar to the technique proposed for the constrained minimum output energy (CMOE) MUD [8]. This method splits the filter coefficients into two orthogonal components: one which is fixed (equal to the desired user’s signature sequence $s_1$), and another which is adaptive ($w_\perp$).

Standard stochastic gradient techniques can now be applied to this adaptive component, if the gradient descent approach is used, the instantaneous gradient of (6) is taken with respect to $w_\perp$, which is given by

$$\nabla w_\perp = \left(w_\perp^hr - R_2\right)w_\perp^hr$$  \hspace{1cm} (9)

Using (9) and the standard gradient descent iteration, the update step of the LCCMA is given by

![Figure 1. Receiver Model.](image-url)
The amplitudes of all the other transmitting users (MAI) is investigated in figure 4. There is a negligible effect when the desired user’s amplitude does not drop by a factor of less than $1/\sqrt{3}$. When the amplitude is at this level, it is observed that the convergence rate is slower. From figure 4 it is seen that when the amplitude drops below the level, not only is convergence slower, but the receiver is no longer guaranteed to converge towards the MMSE solution (due to the presence of local minima [15]). This phenomenon is evident in the divergence in the SINR curve and the much lower steady state SINR level.

Figure 5 illustrates the marginal increase in BER in the steady state, when a larger step is used. The filter coefficients are assumed to have converged for all simulation runs after 2000 iterations.

Figure 6 importantly demonstrates that if the error in the amplitude estimation is kept to less than the $1/\sqrt{3}$ threshold, then there is a negligible impact on BER.

V. CONCLUSION

The advantages that LCCMA has over the CMOE receiver for the blind MUD of DS-CDMA systems warrant further investigation into its full performance analysis. The dependence on the accuracy of the estimate of the desired user’s amplitude was also demonstrated. The effects of estimation errors were investigated in terms of convergence rate and BER. Convergence analysis of LCCMA when applied to ST-MUD and multipath channels, with estimation errors could prove to be of value.

REFERENCES


**James Whitehead** holds a BScEng (Electronic) and MscEng degree from the University of Natal. At present he is studying a PhD at the University of Natal. His research interests include CDMA systems, with emphasis on multiuser detection and multi-antenna systems.

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Figure 2. The mean of the real (a) and imaginary (b) components of the CMA filter coefficients superimposed on the MMSE coefficient values.

Figure 3. Convergence of LCCMA, with different step sizes $\mu$.

Figure 4. Convergence of LCCMA, with different amplitude values $A$.

Figure 5. BER of LCCMA in steady state (SS), with different step sizes $\mu$.

Figure 6. BER of LCCMA in SS, with different amplitude values $A$. 