

Simulation of Adaptive Blind Multiuser Detector in DS-CDMA Wireless Communication

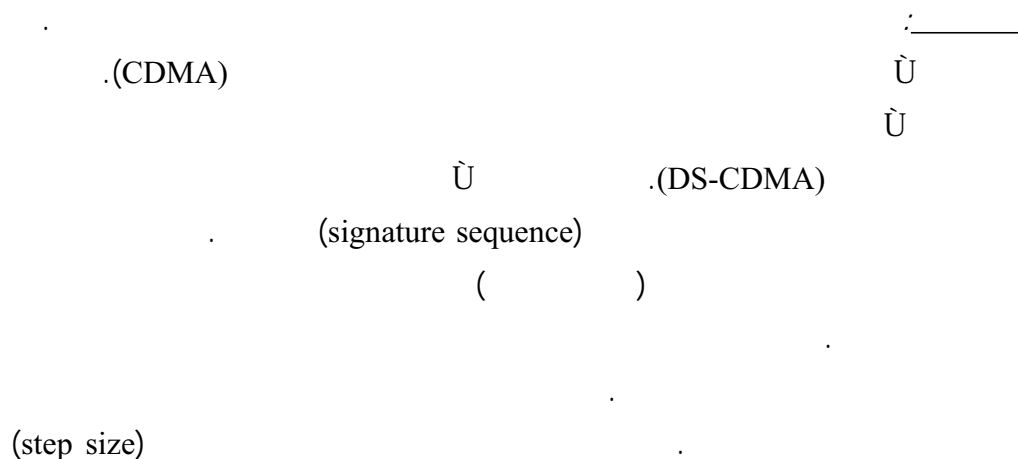
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Abstract:

Multiuser detection is the demodulation of signals of different users interfering with each other. This phenomena known as multiple access interference occurs mostly in code division multiple access (CDMA) systems. In this paper the study and analysis of the blind adaptive multiuser detection algorithm is achieved for direct-sequence code division multiple access (DS-CDMA) communication systems. The goal is to obtain multiuser detectors that require only knowledge of the signature waveform and timing of the desired user. Comparison is performed of the blind adaptive technique with the conventional detector (matched filter detector) or (M.F.D) in perfect power control and in the presence of the near-far effect. In the present simulation, the blind adaptive multiuser detection showed an excellent bit error rate as compared to the conventional detection with the same requirements. Also the blind detector showed an immunity towards the near-far problem. In this simulation the use of adaptive variable step size is used in contrast to the constant step size shows improvement in speed convergence and stability of the algorithm adapted.



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1. Introduction:

Conventional communication models use time or frequency division multiplexing. In time division multiple access (TDMA) systems a unique time slot is reserved for each user. Only one user transmits during the reserved slot and there is no interference between different users. In frequency division multiple access (FDMA) systems, instead of time slots, users are assigned different frequencies in order to prevent interference between users. In code division multiple access (CDMA) systems all users use the same frequency slot simultaneously. Each user is assigned a unique "code" and by using this code receiver can demodulate the desired signal. If these codes are orthogonal and the users are perfectly synchronized it is possible to demodulate the signal free from multi-access interference (MAI). Unfortunately there are not many orthogonal codes and even if orthogonal codes are used it is a difficult task to synchronize all users in a mobile environment. Therefore for practical applications MAI always exists in CDMA system. It is shown that in cellular environments CDMA has a higher capacity than other schemes but MAI is the limiting factor of this capacity. For traditional communication methods matched filter is known to maximize the signal-to-noise ratio. It will be shown that matched filter approach is not very effective against MAI. In a mobile environment a particular user's signal may be received more strongly than the desired user. This effect is known as the near-far effect. Matched filter's performance in such conditions is very poor [1].

To combat MAI the nature of the MAI must be considered at the demodulation. The optimum detector was proposed by Verdu'. Unfortunately this receiver has a very high computational complexity that increases exponentially with the number of active users. Other receivers are proposed which are simpler in terms of computational complexity. Usually these receiver's performances are not as good as the optimum detector. One of the suboptimum detector is the decorrelating detector. It can eliminate all MAI provided that the signature waveforms are linearly independent. However while eliminating MAI it increases the noise power. Another type of suboptimum detector is the MMSE detector. It is designed to minimize the mean-square error between the filter output and the transmitted bit. Suboptimum detectors require knowledge about the interference parameters (powers, signature waveforms, timing... of the interferer) and usually these parameters are either not available or changing very rapidly in practical applications. Therefore simpler receivers that can also track changes in channel conditions are desired.

Some adaptive algorithms use training sequences which are bit sequences that are known at the receiver. They carry no information and hence their transmission is a waste in bandwidth. Adaptive MMSE detector is a typical detector that uses training sequences to minimize the square error between the transmitted bit and the filter output. Each time the channel goes through drastic changes the training sequence must be retransmitted which is a very costly operation for fast changing channels like the wireless environment. To overcome this problem blind detectors are proposed. The blind detectors only require the signature waveform and the timing of the desired user [2].

2.2. Synchronous CDMA system Model

In this paper continuous- and discrete-time models are given for a synchronous short code CDMA system with a total number of K users that transmit bits using binary antipodal modulation over a white Gaussian noise channel. In synchronous channel model the beginning and ends of a bit transmission are the same for all users [4].

2.2.1. Continuous-time Model

The basic synchronous K -user CDMA model describes the received signal of a CDMA system in which K synchronous bit streams antipodally modulate K signature waveforms, which are transmitted over an Additive White Gaussian Noise (AWGN) channel. Both the bit streams and the signature waveforms are represented by nonreturn-to-zero (NRZ) signals. The received signal for one symbol period in such a system can be expressed as:

$$r(t) = \sum_{k=1}^K A_k b_k s_k(t) + \sigma n(t) \dots \dots \dots (1)$$

Where

$r(t)$: Received signal

$s_k(t)$: Is the deterministic signature waveform assigned to the k th user, normalized to have unit energy

$$\|s_k\|^2 = \langle s_k, s_k \rangle = \int_0^T s_k^2(t) dt \underline{\underline{=}} 1 \dots \dots \dots (2)$$

The signature waveforms are assumed to be zero outside the interval $[0, T]$, and therefore, in an AWGN channel, there is no inter symbol interference.

A_k : Is the received amplitude of the k th user's signal. Is A_k^2 referred to as the energy of the k th user.

$b_k \in \{-1, +1\}$ is a bit transmitted by the k th user.

$n(t)$: Is white Gaussian noise with zero mean and unit variance. It models thermal noise plus other noise sources unrelated to the transmitted signals.

σ : The standard deviation of the noise.

2.2.2. Discrete-time CDMA Model

CDMA detectors commonly have a front-end whose objective is to obtain a discrete-time representation of the received continuous-time waveform $r(t)$.

One way of converting the received waveform into a discrete-time representation is to pass it through a bank of matched filters, each matched to the signature waveform of different user. The outputs of the matched filters are then sampled at the end of each bit period.

The output of the matched filter for a user k for synchronous CDMA is expressed as:

$$y_k = \int_0^T r(t)s_k(t)dt$$

$$= A_k b_k \int_0^T s_k(t)s_k(t)dt + \sum_{j \neq k} A_j b_j \int_0^T s_j(t)s_k(t)dt + \sigma \int_0^T n(t)s_k(t)dt \quad \dots\dots\dots(3)$$

Where suffix j denote the interfering signal

By using the fact that $s_k(t)$ is normalized to have unit energy the matched filter outputs can be expressed as:

$$y_k = A_k b_k + \sum_{j \neq k} A_j b_j \rho_{jk} + n_k \quad \dots\dots\dots(4)$$

Where,

$$\rho_{jk} \triangleq \langle s_j, s_k \rangle = \int_0^T s_j(t)s_k(t)dt \quad \dots \quad \dots \quad \dots \quad (5)$$

and

$$n_k \triangleq \sigma \int_0^T n(t)s_k(t)dt \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (6)$$

is a Gaussian random variable with zero mean and variance equal to σ^2 .

3. BLIND ADAPTIVE MMSE DETECTION:

In this section a description of the mathematical background and the implementation algorithm for the adaptive blind multiuser detection technique. Also attention is paid to minimize the mean output energy (MOE).

3.1. Linear Multiuser Detectors

The blind adaptive MMSE detector is an example of a linear multiuser detector. Linear multiuser detectors apply a linear transformation to the outputs of the matched filter bank to produce a new set of outputs, which hopefully provide better performance when used for estimation. Other examples of linear multiuser detectors are the conventional, decorrelating and MMSE detector [1]. Since matched filtering is also a linear operation, the matched filter bank followed by a linear transformation used in linear multiuser detection can be seen as a matched filter bank with modified sequences. So the signature sequence s is replaced by a modified

signature sequence c . A linear multiuser detector for user 1 can be characterized by the modified sequence c_1 , which is the sum of two orthogonal components. One of these components is the signature sequence of user 1 (s_1). The other component is denoted as x_1 and will be referred to as the x sequence, so

$$c_1 = s_1 + x_1 \dots\dots\dots (7)$$

With $c_1, s_1, x_1 \in \mathfrak{R}^N$, where \mathfrak{R}^N is the vector matrix and N is the number of chips per symbol and

$$\langle s_1, x_1 \rangle = 0 \dots\dots\dots (8)$$

Since x_1 is orthogonal to s_1 , any x_1 can be chosen to minimize the correlation between the multiple access interference and c_1 , while the correlation with user 1 remains constant. Thus

$$\langle s_1, c_1 \rangle = \langle s_1, s_1 + x_1 \rangle = \langle s_1, s_1 \rangle + \langle s_1, x_1 \rangle = 1 \dots\dots\dots (9)$$

The linear detector makes its decision for user 1 which is based on the signum of the output of the matched filter with modified sequence, so

$$\hat{b}_1 = \text{sgn} (\langle r, c_1 \rangle) \dots\dots\dots (10)$$

Where \hat{b}_1 is the transmitted bit estimation.

Every linear multiuser detector can be written as in equation (7) to (9), so it is a canonical representation for linear multiuser detectors [2].

The output of the matched filter with modified sequence for user 1 is equal to:

$$y_1 = \langle r, c_1 \rangle = A_1 b_1 \langle s_1, s_1 + x_1 \rangle + \sum_{k=2}^K A_k b_k \langle s_k, s_1 + x_1 \rangle + \sigma \langle n, s_1 + x_1 \rangle \dots\dots\dots (11)$$

Where A_1 is the amplitude of user 1 and using $\langle s_1, s_k \rangle = \rho_{1k}$ gives the

$$y_1 = A_1 b_1 + \sum_{k=2}^K A_k b_k (\rho_{1k} + \langle s_k, x_1 \rangle) + \sigma \langle n, s_1 + x_1 \rangle \dots\dots\dots (12)$$

3.2. Minimizing Mean Output Energy

The blind adaptive MMSE detector in fact minimizes the mean output energy (MOE). The mean output energy of a linear multiuser detector for user 1 is defined as:

$$MOE(x_1) \triangleq E \left[\left(\langle r, s_1 + x_1 \rangle \right)^2 \right] \dots \dots \dots (13)$$

The trivial solution to minimizing this equation is setting $c_1 = 0$. However, since c_1 is defined as the sum of s_1 and x_1 , this solution is eliminated. It can be expected intuitively that minimizing the output energy of the linear detector is a sensible approach. This is because the energy at the output of the detector can be written as the sum of the energy due to the desired signal plus the energy due to the interference (background noise and multiple access interference). Any x_1 , as long as x_1 is orthogonal to s_1 , can be chosen to minimize the interference, but it will not influence the energy of the desired signal. The x_1 that minimizes the mean output energy also minimizes the mean square error as the following reasoning shows.

In MMSE detector require equation (13) to be minimized.

$$MSE(x_1) = E \left[\left(A_1 b_1 - \langle r, s_1 + x_1 \rangle \right)^2 \right] \dots \dots \dots (14)$$

The following fact can be observed

$$MSE(x_1) = MOE(x_1) - A_1^2 \dots \dots \dots (15)$$

So the mean square error and the mean output energy differ by only a constant and the arguments to minimize both functions are the same. To execute equation (14), knowledge of the data bits for user 1 is needed. For an implementation of the MOE function this knowledge is not needed, which means that an algorithm based on the MOE function does not require training sequences [3, 4].

3.3. Blind Adaptation Rule [2, 3]

The adaptation rule for blind adaptive multiuser detector for user 1 can be written as:

$$x_1[i] = x_1[i-1] - \mu Z_1[i] (r[i] - Z_{mf1}[i] s_1) \dots \dots \dots (16)$$

Where

$r[i]$: Received signal for the bit period of the i th bit.

$x_1[i]$: The value of the x sequence obtained in the i th bit of iteration.

$x_1[i-1]$: The value of the x sequence obtained during previous iteration of the algorithm from the previous received signal $r[i-1]$.

$Z_1[i]$: The output of the adaptive filter for the i th bit period.

$Z_{mf1}[i]$: The output of the matched filter for the i th bit period.

μ : Step size.

To minimize the mean output energy (MOE) given in equation (13), the x sequence is to adapt each bit period using the stochastic gradient descent algorithm. Since subscripts are already used to indicate users the iteration number is indicated with an index $[i]$.

The output of the matched filter for the i th bit period is written as:

$$Z_{mf1}[i] = \langle r[i], s_1 \rangle \dots \dots \dots (17)$$

Analogously, the output of the adaptive filter for the i th bit period is written as:

$$Z_1[i] = \langle r[i], s_1 + x_1[i-1] \rangle \dots \dots \dots (18)$$

The output of the adaptive filter $Z_1[i]$ is used as the decision statistic of the blind adaptive MMSE detector for user1:

$$\hat{b}_1 = \text{sgn}(Z_1[i]) = \text{sgn} \langle r[i], s_1 + x_1[i-1] \rangle \dots \dots \dots (19)$$

The natural choice for initialization of the x sequence is $x_1[0] = 0$ in equation (16). Whether the algorithm is stable or not stable depends on the value for the step size μ . A smaller step size will result in a longer adaptation time. On the other hand, a smaller step size will also result in a $x_1[i]$ which is closer to $x_{1,opt}$, where $x_{1,opt}$ is the orthogonal sequence component that results in a global minimum of the mean output energy. So the best value for μ is a trade-off between adaptation time and accuracy [5].

4. Results and Discussion:

In this section a description of the simulation model for synchronous DS-CDMA for $K=10$ -user, processing gain $N=31$ short code [the period of the signature sequence is equal to the duration of a bit], gold code sequence is used, with Additive White Gaussian Noise (AWGN) [3].

4.1. Results

In figure 1 the Bit-Error-Rate (BER) simulation results of the conventional, blind adaptive MMSE and linear MMSE detectors are compared for a range of Signal-to-Noise Ratio (SNR) for a 10-user with perfect power control.

In figure 2, the same parameters used in figure 1 except for imperfect power control (near-far effect), in which the amplitudes of the interfering users are 10-dB larger than the desired user, (where the Near-Far Ratio

(NFR) is defined as $20 \log_{10}(A_k/A_1)$. This figure gives an indication of the near-far effect of the detection techniques.

Figure 3 shows the bit-error rate for the desired user of the conventional and blind adaptive MMSE detectors as a function of the Near-Far Ratio (NFR) for SNR=10 dB. Figures 4 and 5 shows the Signal-to Interference Ratio (SIR) as a function of the numbers of iterations. The SIR is defined to be the ratio of the desired signal power to the sum of the powers due to noise and MAI at the output of the filter [2]. Figure 4 and 5 show the convergence speed of the Least Mean Square (LMS) algorithm for two cases. The first case in figure 4 uses fixed step size (μ). While in figure 5 uses variable step size. After many trail the choice of the value of μ is such that the algorithm adaptation is stable and accurate.

4.2 Discussion

The figure 1 clearly shows that the blind adaptive detector achieves a far lower bit-error-rate than the conventional detector (M.F.D) for the same signal-to-noise ratio. Also the blind adaptive detector achieves nearly the same bit-error-rat performance as the linear MMSE detector. These results agree perfectly with the results obtained in [3] for a SNR up to 10 dB.

In figure 2 as expected, the conventional detector is affected by a strong interference. Therefore, the conventional detector performance is not good enough in combating multiple access interference. But the blind adaptive detector is found to be robust to strong interference.

In figure 3, the bit-error rate of the conventional detector is improved when the received power of the interfering signals where smaller than the desired signal.

From figure 4 and 5, it is clear that it would be better to decrease the step size as the LMS algorithm proceeds. A high value of step size should be used initially to cause fast convergence of the algorithm and then iterations of smaller step size should be used to minimize the ripple around the optimal value. But great care should be exercised in using adaptive step size [8]. Sometimes the step size may become really small as the algorithm progresses and the $x_{1,opt}$ may never converges to the optimal value. One method of progressively shrinking the step size is to multiply a fixed step size by γ^i where (i) is the iteration number and γ is a number just smaller than 1.

Blind adaptive MMSE detector does not work for long code [signature sequence with a period that is much longer than the duration of a bit] systems, because for each bit it would have to adapt to the section of the signature waveform that is used to modulate that bit. Therefore, the maximal length sequence with length 31 is used to generate the spreading sequences for different users. Since short codes are used the processing gain is also 31. A maximal length sequence with length 31 can generate only 31 different spreading sequences, therefore the simulated systems support 31 users maximum [7].

5. References:

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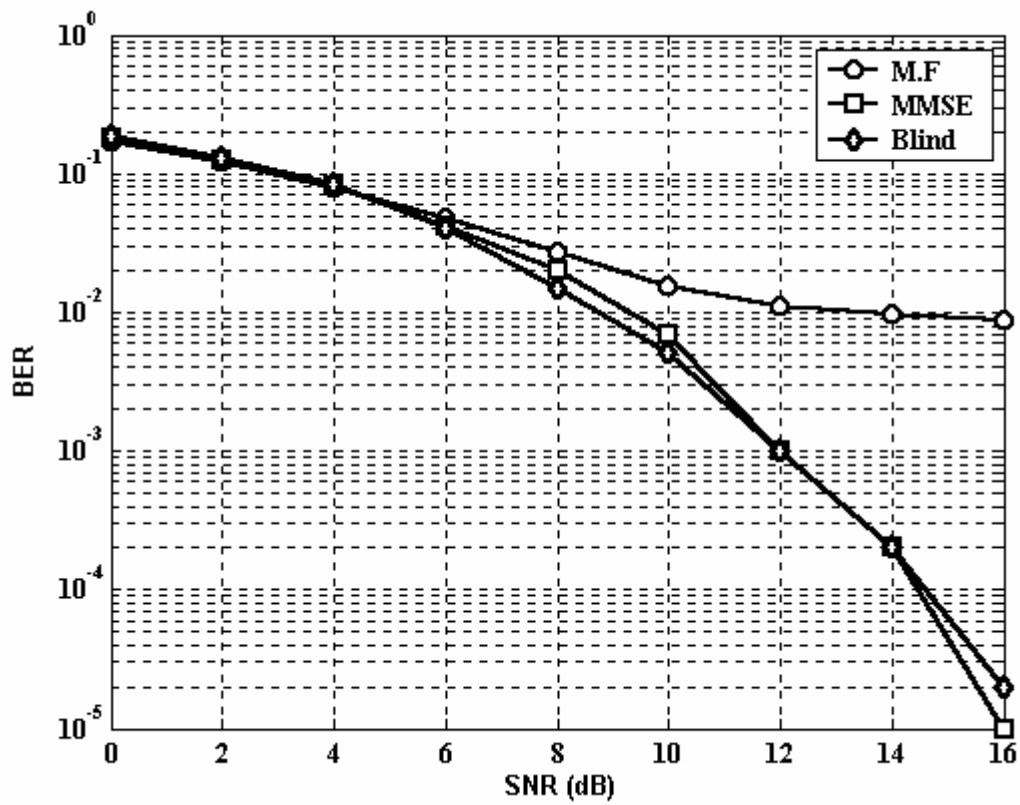


Figure 1 BER/ SNR simulation with perfect power control (PPC), ten users, Processing gain $N=31$.

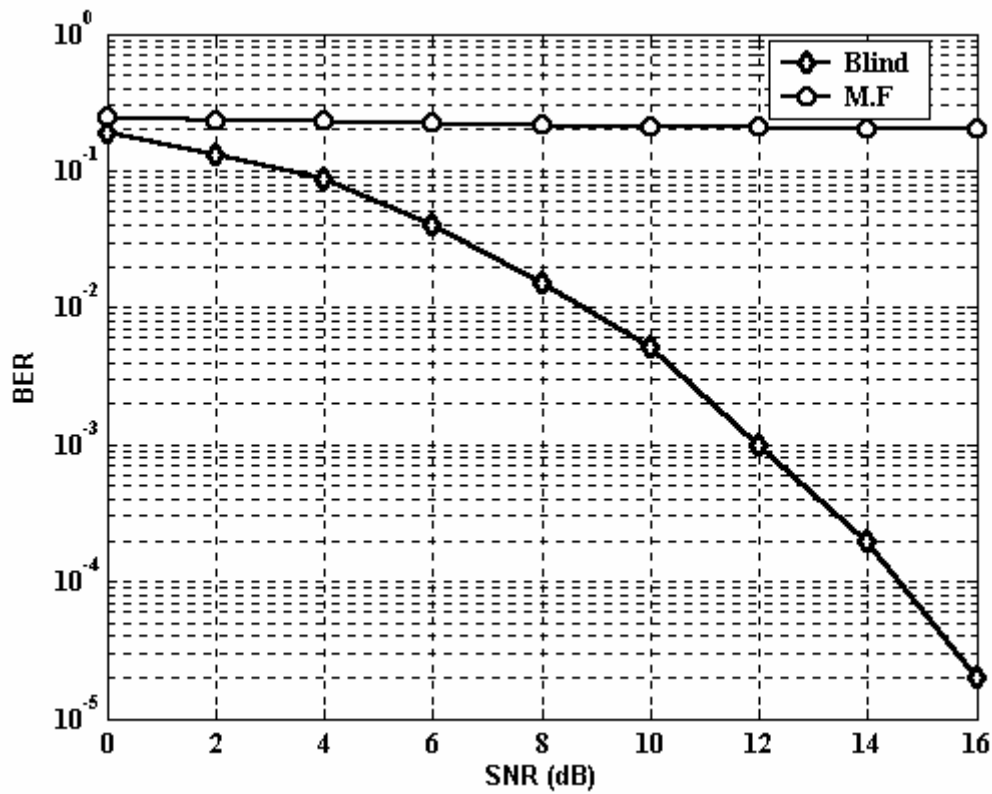


Figure 2 BER/SNR simulation with Near-Far effect ($NFR=10$ dB), ten user, $N=31$.

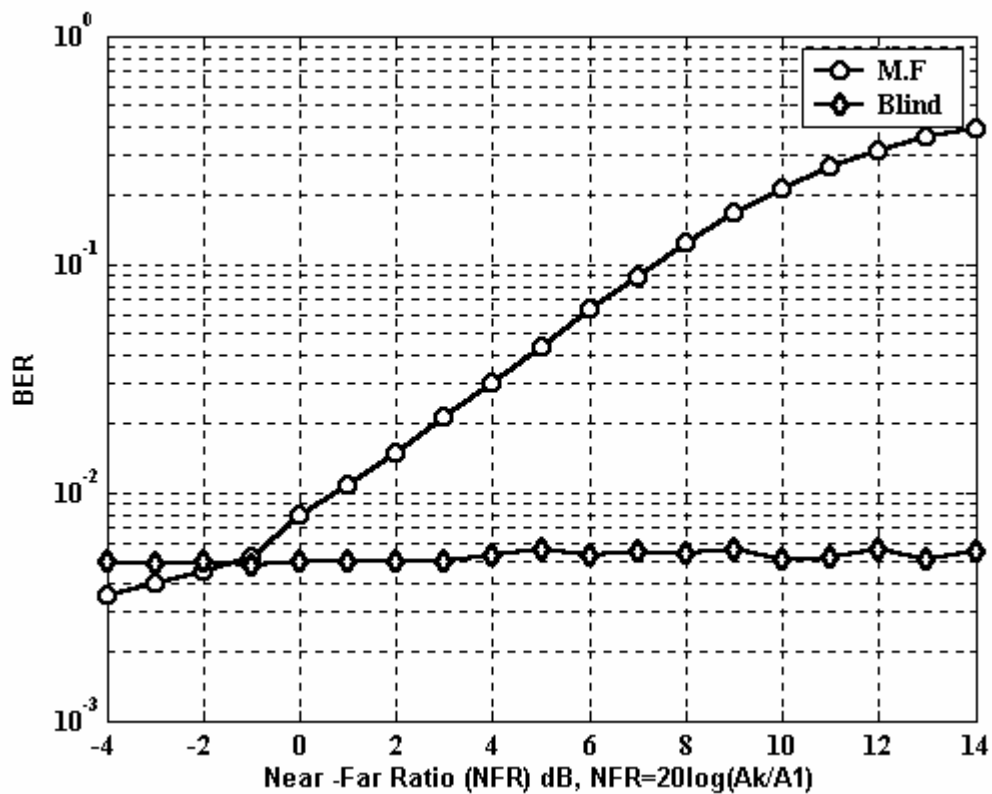


Figure 3 BER/NFR simulation in $SNR=10$ dB, ten user, $N=31$.

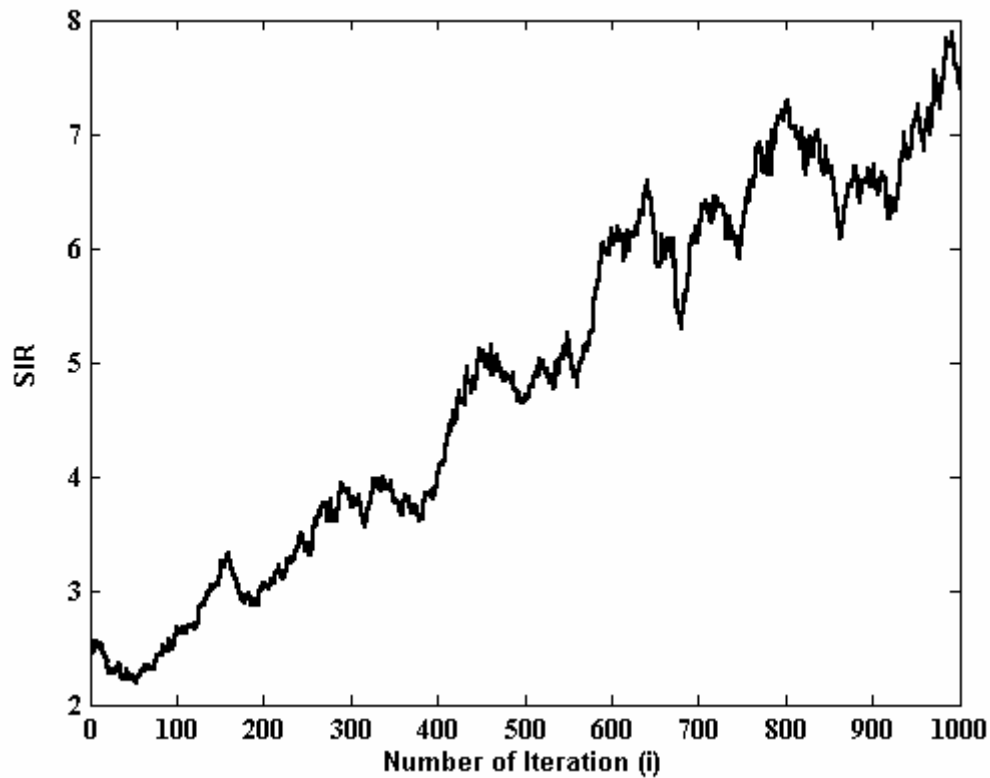


Figure 4 *SIR/number of iteration with constant convergence, $\mu = 0.002$, perfect power control, SNR=10 dB, ten user, N=31.*

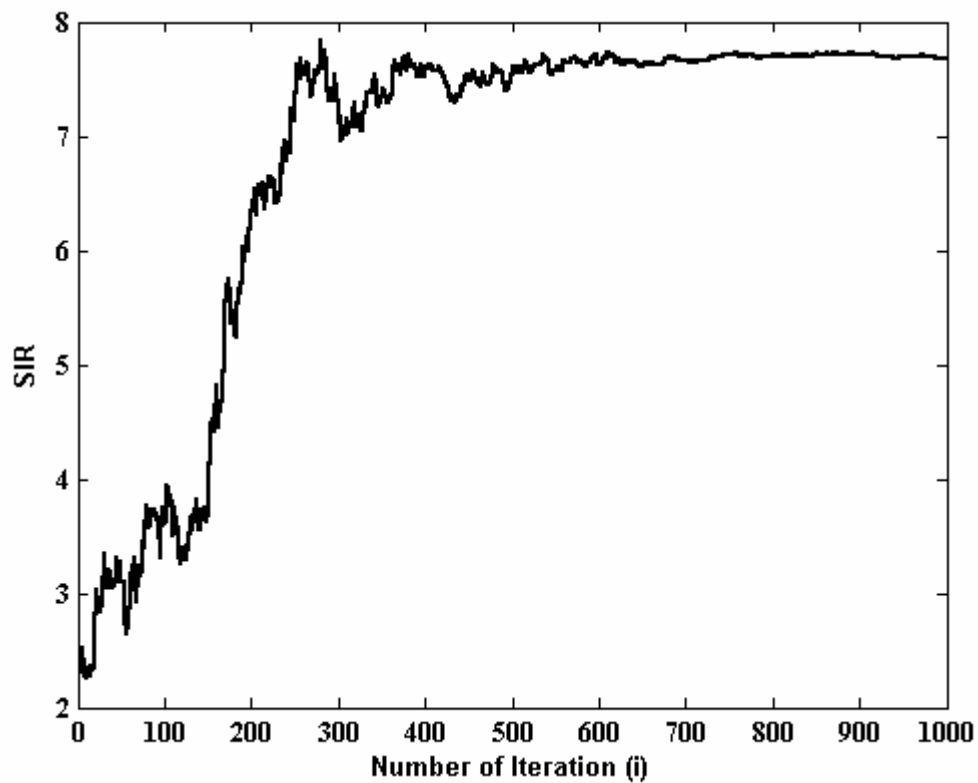


Figure 5 *SIR/number of iteration with variable convergence, $\mu = 0.008$, $\gamma = 0.995$, perfect power control, SNR=10 dB, ten user, N=31.*