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An Adaptive SIC Technique in DS-CDMA using Neural Network

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Abstract

In this paper, we propose an efficient successive interference cancellation (SIC) method in direct sequence code division multiple access (DS-CDMA) system using neural network (NN). Neural network is used here to estimate the amplitudes of different users' signals under frequency selective Rayleigh fading channel. The correlation values between the received signal and the signature /spreading waveforms for different users are given as the inputs to a NN and the output acts as an estimation of corresponding user's signal amplitude. A closed mathematical form of joint probability of error (JPOE) is developed to determine the number of active users' needs to be canceled to achieve a desired bit error rate (BER) value. Simulation results strongly support the mathematical results. Mathematical analysis shows that better performance results can be achieved through large change in weight up-gradation (w) for the strong users with a particular change in learning rate (η). Performance of the SIC system has been studied for initial wrong ordering of a couple of pairs of interfering users based on the correlation values. Simulation results show that BER performance is better when users are ordered based on signal to interference ratio (SIR) values rather than correlation values.

Keywords: SIC, Neural Network, DS-CDMA; JPOE;

1. Introduction

Recently code division multiple access (CDMA) has become a potential solution to support multimedia services in mobile radio communications. CDMA systems have an interesting property that their capacity is typically limited by multiple-access interference (MAI), rather than noise [1]. Thus MAI in CDMA puts a limit on capacity while an acceptable value of bit error rate (BER) performance of the system is considered. Multiuser detection (MUD) in various forms such as successive interference cancellation (SIC) [2], parallel interference cancellation (PIC) [3], partial PIC (PPIC) [4], block PIC (BPIC) [5] etc. are used to mitigate the effect of MAI. Performance results are reported along with the merits and the demerits of each one in terms of BER, computation cost and complexity, time complexity and hardware requirement. SIC offers intrinsic advantages such as potential compatibility with current commercial systems, allows of strong error-correcting codes, and is robust in an asynchronous environment [6], along with the requirement of minimum amount of additional hardware compared to PIC. However, SIC suffers from typical problems namely (i) one additional bit delay per stage cancellation is required which leads to larger delay problem in order to achieve desired BER, (ii) significant deterioration in BER performance occurs if initial estimation of signal strength for different users are not reliable and (iii) performance largely depends on reordering of the signals whenever the power delay profile of radio mobile channel changes. A trade off must be made between (i) the

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number of users that are canceled sacrificing in BER value and the amount of delay that can be tolerated; and at the same time (ii) the precision of power ordering and the acceptable processing complexity. So there must be a provision to overcome the effect of non-reliability in the initial data estimates. Performance improvement in SIC at an acceptable level of system complexity is possible if estimation of the parameters like amplitude and phase for the transmitted data is done accurately. This can be accomplished through adaptive learning.

Literature on MUD is quite rich. The optimum multiuser detector proposed in [1] achieves significant performance improvement relative to single user receiver but the computational complexity increases exponentially with the number of users. This has motivated the use of low complexity linear [7] and decision driven suboptimal multiuser detection techniques. Several SIC schemes are reported in literature, like Fang and Milstein propose [2] SIC in convolution coded multicarrier DS-CDMA systems, Dua et al. [8] propose two minimum probability of error-based space-time multiuser detection algorithms, Yen and Hanzo propose [9] Genetic algorithm assisted joint multiuser symbol detection and fading channel estimation for synchronous CDMA systems. An optimal power control algorithm for MC-CDMA with SIC is derived in [6], allowing analytical bit-error rate expression to be found for an uncoded system. Low-rate forward error corrections are added to the system to achieve robustness. The first algorithm in [8], minimum joint probability of error (MJPOE), aims to minimize the joint probability of error for all users, while the second algorithm, minimum conditional probability of error (MCPOE), minimizes the probability of error of each user conditioned on the transmitted bit vector, for each user individually. Bhattacharya and Biswas propose [10] two stage interference cancellation scheme where detectors switch dynamically from SIC to RAKE depending on the channel characteristics and many others. They argue that at low SNR, SIC behaves in the same manner as match filter but for high SNR values, RAKE receivers are deployed to achieve better capacity than conventional detectors.

The discussion in the previous section indicates that all the proposed algorithms of multiuser detection mostly focus on throughput improvement along with reduction in computation complexity. The algorithms do not study the performance for unknown and time varying channel parameters. Important system design issues such as multipath, latency, and estimation error have often been neglected. The issues are mostly taken care by adaptive multiuser detector system. Although blind adaptive multiuser detectors have the advantage that they eliminate the need for a training sequence in adaptation mode leading to savings in bandwidth, but the overall system design is complicated and not many wireless standards today use blind algorithms.

In this paper, an adaptive SIC technique in DS-CDMA using neural network [11] is proposed. First a learning algorithm is developed using single layer or multi layer feed forward neural network for some known data sets (using supervised learning method). Then this network is used to estimate the user signal's amplitudes under Rayleigh fading channel. Performance of the system has been studied using variable learning rate. Mathematical analysis shows that weight updatation for the strong users must be higher compared to weak users. This effect of mathematical analysis is used for performance improvement. A closed loop analytical form of joint probability of error (JPOE) for this system is also developed. This helps to calculate the interfering effect of the required number of users to be cancelled, out of a given number of active users, aiming to achieve a certain acceptable JPOE value. Simulation results strongly support the mathematical results. Lastly, the effects of initial wrong ordering of the interfering signals based on the correlation values of the different users are also studied. Simulation results show that the proposed adaptive algorithm is capable to solve initial wrong ordering of a couple of pair of users leading to an acceptable level of BER values to achieve.

The rest of the paper is organized as follows. Section 2 describes the system model for synchronous DS-CDMA uplink system. Section 3 presents performance evaluation. Conclusions are drawn in Section 4 along with the scope of future work.

2. System Model for Synchronous DS-CDMA

We assume that DS-CDMA system with K number of active users like to transmit their information asynchronously over a common additive white Gaussian noise (AWGN) channel. The received signal impinging on a single antenna element at the base station can be modeled as,

$$r(t) = \sum_{j=1}^{K} \sum_{i=-\alpha}^{\alpha} A_j \alpha_j b_j(i) S_j(t - iT - \tau_j) + n(t) \quad (1)$$

where A_j and $b_j(i)$ are the amplitude of the j^{th} user transmitted signal and i^{th} symbol (±1), respectively in t € [iT, (i+1)T], T is the bit interval, τ_j is the time delay for the j^{th} user's received signal, α_j is the j^{th} user's channel gain, $S_j(t)$ is the signature waveform of the j^{th} user and n(t) is the AWGN with zero mean and a two sided power spectral density (PSD) of σ^2 W/Hz.

The following additional properties are also assumed;

(i) The signature waveforms are time limited in [0, T] i.e. Sj(t) = 0 for t € [0, T].

(ii) Each signature/spreading waveform has unit energy and $\int_0^T S_j^2(t)dt = 1$ for all j.

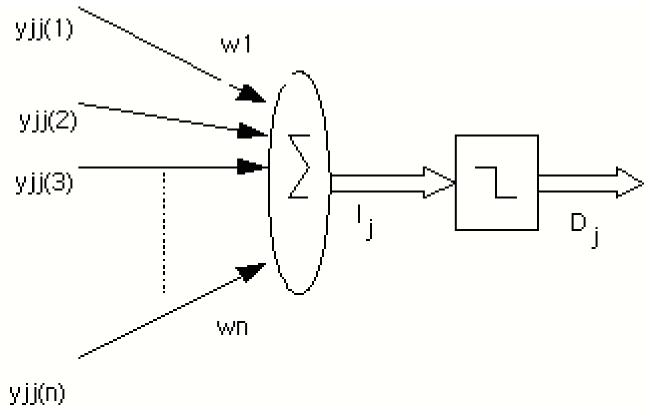

Fig. 1 Neural network based amplitude estimation for j-th user

In case of SIC receiver, the first task is to arrange the received signals according to their signal strengths. We have assumed here that the correlation value between the received signal of j^{th} user with its signature waveform $S_j(t)$ reflects it's signal strength. Though it is an approximation, but it is good enough for initial assumption. Fig. 1 shows neural network based amplitude estimation for the j-th user. Now correlation vector for the j^{th} user,

$$y_{jj} = \langle r(t), S_j(t) \rangle = A_j \alpha_j b_j + \sum_{l=1, l\neq j}^{K} \rho_{l,j} A_l \alpha_l b_l + n_j \tag{2}$$

Where $\rho_{l,j}$ is the cross-correlation between the l^{th} and j^{th} user's signature waveforms given by $\rho_{l,j} = \int_0^T S_j(t) S_l dt$

n_j = complex Gaussian with zero mean, $E[n_i \; n_j^*] = 2\sigma^2$ when j = 1and $E[n_i \; n_j^*] = 2\sigma^2 * \rho_{l,j}$ when $j \neq 1$.
Mathematically the summation unit's output can be expressed as,

$$I_j = \sum_{S=1}^{n} W_S * y_{jj}(s) = \sum_{S=1}^{n} W_S * [A_j \alpha_j b_j(s) + \sum_{l=1,l\neq j}^{K} \rho_{l,j} A_l \alpha_l b_l(s) + n_j(s)] \tag{3}$$

$$= \sum_{S=1}^{n} W_S * A_j \alpha_j b_j(s) + \sum_{S=1}^{n} I_{OS} + \sum_{S=1}^{n} I_{NS} \tag{4}$$

Where $I_{OS} = W_S * \sum_{l=1,l\neq j}^{K} \rho_{l,j} A_l \alpha_l b_l(s)$ is the interference due to the users other than j^{th} user and $I_{NS} = W_S * n_j(s)$ is the interference due to noise.

Here w_s (also denoted as w_i in subsequent analysis) is the weight factor associated with i^{th} bit, I_j is the output of the summation unit and D_j is the output of neuron for the j^{th} user. Back propagation algorithm is now applied to adjust the weight factors $w_1, w_2, \ldots w_n$, with target output for j^{th} user is $T_j = A_j \alpha_j$. But the computed output for j^{th} user by the neuron is $O_j = D_j = \hat{A}_j \hat{\alpha}_j$. So, the Error signal is

$$E_j = ½ [T_j – O_j]^2 = ½ [A_j \alpha_j – O_j]^2 \tag{5}$$

According to gradient descend law, the weight factors must be updated with the amount $\Delta W = -n * \frac{\partial E}{\partial W}$

η = learning rate parameter, $\frac{\partial E}{\partial W}$ is the gradient of the error. So, for i^{th} bit, the corresponding weight will be updated at a time with the amount,

$$\Delta W_i = -n * \frac{\partial E_j}{\partial W_i} \tag{6}$$

According to the chain rule we can write $\frac{\partial E_j}{\partial W_i} = \frac{\partial E_j}{\partial D_j} \cdot \frac{\partial D_j}{\partial I_j} \cdot \frac{\partial I_j}{\partial W_i}$ (7)

Actually Dj is the final output of the neuron obtained after passing through a non-linear filter, known as *activation function*. Here sigmoid function is used as activation function and is written as follows:

$$D_j = 1/(1 + \exp(-\lambda I_j)) \tag{8}$$

where λ = sloping parameter. We also know that

$$I_j = W_1 * Y_{jj}(1) + W_2 * Y_{jj}(2) + \ldots\ldots\ldots + W_n * Y_{jj}(n) = \sum_{i=1}^{n} W_i Y_{jj}(i) \tag{9}$$

Differentiating Eqs. (5), (8) and (9) w.r.t D_j, I_j and W_j, respectively and putting them in Eq. (7), we have

$$\Delta W_i = + \eta * \lambda * D_j * Y_{jj}(i) * (1 - D_j) * (A_j * \alpha_j – D_j) \tag{10}$$

According to back propagation algorithm, after 't+1' number of iterations, i^{th} weight factor will be updated to

$$[W_i]^{t+1} = [W_i]^t + [\Delta W_i]^{t+1}$$

Using a variable learning rate (η_i), the rate of change of ΔW with respect to η can be written as follows:

$$\frac{\partial \Delta W_i}{\partial \eta_i} = [\lambda * Y_{jj}(i) * \exp(-\lambda I_j) * A_j * \alpha_j * (1 + \exp(-\lambda I_j)) - 1]/[L] \tag{11}$$

where $L = [1 + \exp(-\lambda I_j)]^3$. From the above Eq. (11), we can say that rate of change of ΔW_i with respect to η_i is largely effected by the term $(A_j * \alpha_j)^2$. This suggests that the stronger users weight updatation must be higher.

2.1 Mathematical Expression for JPOE

Let us assume that in an SIC receiver interference due to 'm' number [m ≤ K] of users must be canceled to get desired joint probability of error (JPOE). We now consider 'n' numbers of correlation values of jth user (corresponding to 'n' no of bits) are the inputs to the neural network for getting the output as the estimation of the j^{th} users amplitude. Finally we get the estimated amplitude,

$$\hat{A}_j * \hat{\alpha}_j = h * \varphi(I_j) = h * 1/(1 + \exp(-\lambda I_j)) \tag{12}$$

After canceling the 'm' users' interferences, the received signal becomes,

$$r^m(i) = \sum_{l=m+1}^{K} A_l * \alpha_l * b_l(i) * S_l(t - iT - \tau_l) + \sum_{l=1}^{m} [A_l * \alpha_l * b_l(i) - \hat{A}_l.\hat{\alpha}_l.\hat{b}_i(i)] S_l(t - iT - \tau_l) + n(i) \quad (13)$$

The interfering signal due to the rest of the users would be detected by match filtering; correlation vector for k[th] user, where [m<k≤K] and bit decision of i[th] bit for k[th] user are given by Eq. (14) & Eq. (15), respectively as follows:

$$y_{kk} = \langle r^m(t), S_k(t) \rangle = A_k * \alpha_k * b_k + \sum_{l=m+1, l\neq k}^{k} \rho_{lk} * A_l * \alpha_l * b_l + \sum_{l=1}^{m} \rho_{lk} (A_l * \alpha_l * b_l - A_l^{\wedge} * \alpha_l^{\wedge} * b_l^{\wedge}) + n_k \quad (14)$$

and $\hat{b}_k(i) = \mathrm{sgn}[y_{kk}(i)]$ (15)

Let $\hat{b} = [\hat{b}_{m+1}, \hat{b}_{m+2}, \ldots\ldots.\hat{b}_k]^T$ denotes the estimated bit vector, where $\hat{b}_k$ denotes the estimated bit for k[th] user when [$m < k \leq K$]. Assuming that all bit vectors are equally likely (with probability p= $\frac{1}{2^{(K-m)}}$), JPOE P_E can be expressed as,

$$P_E = \sum_{\forall b} p(\hat{b} \neq b / b) p(b) = \sum_{\forall b} [1 - p(\hat{b} = b / b)](1/2^{(K-m)}) = 1 - (1/2^{(K-m)}) \sum_{\forall b} p(\hat{b} = b / b) \quad (16)$$

For large number of bits, each correlation vector of $y_s = [y_{m+1,m+1}, y_{m+2,m+2}, \ldots\ldots., y_{k,k}]^T$ tends to have Gaussian distribution and probability density function (pdf) can be expressed as follows:

$$p_{ys}(x_k) = 1/\sqrt{(2\pi)\sigma_k} * e^{-(x_k - \mu_k)^2 / 2\sigma_k^2} \quad (17)$$

where the mean and variance values are given by $\mu = [\mu_{m+1}, \mu_{m+2}, \ldots\ldots., \mu_k]^T$ and by $\sigma^2 = [\sigma_{m+1}^{2,}, \sigma_{m+2}^2, \ldots\ldots\ldots, \sigma_k^2]^T$, respectively.

Now $p(\hat{b} = b / b) = \int_{Lm+1}^{Um+1} \ldots \int_{LK}^{UK} .. \prod_{k=m+1}^{K} p_{ys}(x_k) dx_{m+1} \ldots dx_k$ (18)

where LK = 0, UK = ∞ if b_k = 1 and LK = $-\infty$, UK = 0 if b_k = -1.Now the expression of JPOE is given by

$$P_E = 1 - (1/2^{(K-m)}) * \sum_{\forall b} \int_{Lm+1}^{Um+1} . \int_{LK}^{UK} 1/\sqrt{(2\pi)}\sigma_k * e^{-(x_k - \mu_k)^2 / 2\sigma_k^2}$$

$$P_E = 1 - (1/2^{(K-m)} * \sum_{\forall b} [\prod_{k=m+1}^{K} Q(-b_k * \mu_k / \sigma_k)] \quad (19)$$

where $Q(x) = 1/\sqrt{(2\pi)} * \int_x^{\infty} e^{(-t^2/2)} dt$.

The function Q(x) is the complementary error function.

3. Performance Evaluation

This section presents performance results obtained through MATLAB simulation for the proposed NN based adaptive SIC in DS-CDMA. Each user's channel has been modeled as slow frequency selective Rayleigh fading channel. Fig. 2 shows the effect of the number of user's signal cancellation on BER performance at different SNR, where number of bits per users is 1000, process gain (PG) is 23 dB and 50% users' signal are cancelled. Results show that average

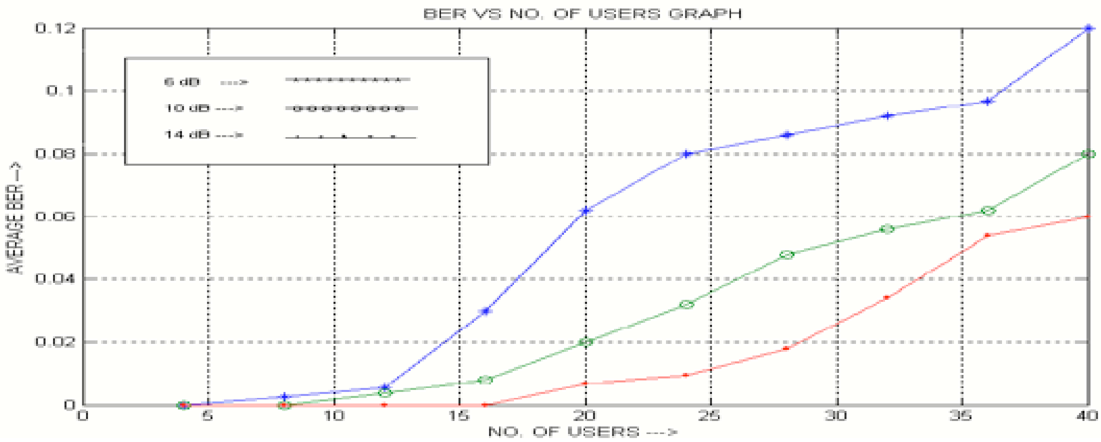

Fig. 2 Average BER vs number of users at different SNR values when 50% users' interfering effect is cancelled

BER increases with the increase of number of users due to an increase in MAI and decreases with the increase of SNR values. Fig. 2 shows the graphical result for JPOE vs number of users at SNR 10 dB with process gain 23 dB and number of bits per user is 1000. Here at first BER is calculated for each user after canceling 50% user's interference from the received signal. Then the minimum value of BER (expected for the strongest user) is assumed as JPOE for all users. Now number of users for which interference cancellation (IC) must be done, out of total number of users, is calculated so that BER for each user must lie below the JPOE value.

Table1: Average BER corresponding to number of users with Interference Cancellation and Match Filtering

IC done for the no. of users	MF done for no. of users	Average BER
20	0	0.0055
16	4	0.0315
12	8	0.0410
8	12	0.0540
4	16	0.0645
0	20	0.1320

Table 1 shows the number of users for which interference cancellation (IC) done, number of users for which match filtering done and corresponding average BER values at SNR=10 dB. Results show that as the number of users for which interference cancellation done decreases, average BER value increases. Results also show that when 20% of the total active user's interfering signal is cancelled, BER value obtained decreases to an acceptable value. It is observed that there is no significant improvement in BER when more number of users' interfering signals are cancelled. This shows that learning algorithm reduces the inherence delay problem (as less number of interference cancellation required) of SIC in order to achieve an acceptable BER value. Table 2 shows how the adaptive algorithm takes care initial wrong ordering of the signal strength of the users. We have tested the performance of the proposed method by changing the initial ordering of the several pairs of users where (a, b) indicates the users 'a' and

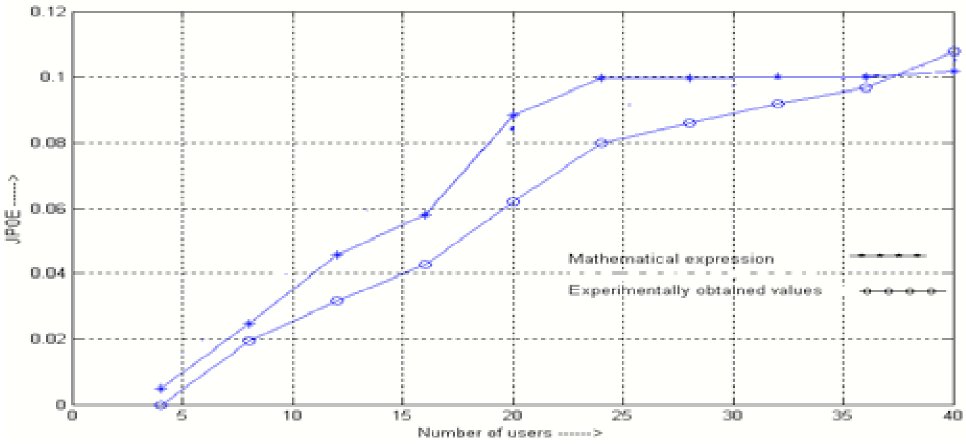

Fig. 3 JPOE vs number of users

‘b’ have changed their positions. Simulation results show that BER values do not change significantly even if large number of pairs change their positions. Simulation results also show that learning algorithm keeps BER to an acceptable level even when eight users are ordered wrongly out of twenty users.

Table 2: BER performance after change in initial ordering of the users based on signal strength at the receiver

No. of interchange performed	Between pair of users	BER
0	None	0.02000
1	(1 & 4)	0.03010
2	(1 & 3), (2 & 5)	0.05100
3	(1 & 2), (3 & 4), (5 & 6)	0.04800
4	(1 & 8), (2 & 7), (3 & 6), (4 & 5)	0.06800

4. Conclusions and scope of future work

This work analyzes performance of MUD using NN based SIC technique in DS-CDMA. Performance of the proposed adaptive algorithm is studied under various observations. It has been observed that the learning from the correlation values of the received signal with the spreading codes causes significant improvement over conventional SIC at the cost of a slight increase in complexity. The performance is improved with the increase of hidden layers inside the NN, in other words, by increasing the complexity. This concept is very effective when the numbers of users are very large. BER performance is also improved using variable learning rate. It is also observed that the system is able to tackle the problem of wrong ordering of the user signals according to their signal strengths by learning itself from the environment. A closed loop analytical form of JPOE for this particular system is developed and given a particular number of active users (K), how many users' signals need to be canceled in order to obtain a desired JPOE is also derived. Simulation results closely support the mathematical results. Future work may be carried out for power management among the users by extending the proposed learning algorithm in data transmission rate constraint scenario.

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