Multi user detection in CDMA system using Linear and Nonlinear Detector

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Abstract

DS-Code division multiple access is considered as the third generation of cellular mobile used in interim standard 95(IS-95) [1]and it is currently being standardized for universal mobile telecommunication systems (UMTS). CDMA offers attractive features, such as frequency reuse, soft handoff, increased capacity, and multipath combating. In a CDMA system, several users simultaneously transmit information over a common channel using pre-assigned codes. The conventional single user detector consists of a bank of filters matched to the spreading codes. This detector suffers from two problems. First, multiple access interference (MAI) produced by the other co-channel users is a significant limitation to the capacity of this detector. The second problem is the near-far effect which occurs when the relative received power of interfering signals becomes larger. A potential solution is multi-user detection which exploits the information of signals of interfering users. In the present study performance of various linear detectors like matched filter detector, MMSE detector, and adaptive LMS detector are studied. These are the linear detectors that operate linearly on the received signal statistics and are suboptimal detectors. The matched filter bank is the conventional detector and offers the simplest way of demodulating CDMA signals .The detector resulting from the MMSE (minimum mean square error) criterion shows better performance over the conventional one for low SNR value. Adaptive LMS is employed to enhance the BER performance in MUD application.Several factors motivated the research to apply neural network as multi-user detector. NN are nonlinear classifier in addition to being adaptive and computationally efficient. The performance of two layer perceptron neural network using BP learning rule is used for multi-user detection of CDMA signals in AWGN channels. The neural network detectors show improvement of BER in the comparative analysis done in the present work. and offers further research scope for solving multi-user detection problems in CDMA application.

Keywords: MAI, CDMA, MMSE, LMS, NN Detector.

1. INTRODUCTION

The Design and implementation of a high-speed, high-quality, wireless link between two mobile terminals, located anywhere in the world is the challenge being faced by the communications research community today. The dramatic rise of the demand for the wireless mobile communications services over the recent years has emphasized the importance of efficient use of frequency bandwidth. Since the bandwidth available for mobile services is limited, various multiple access techniques have been proposed to increase the channel capacity, i.e. the number of users that can be supported within a specific geographical area. Traditionally, these techniques are based on frequency, time and code allocation.

The technique based on the division of the available spectrum into frequency bands which are then assigned to mobile users is Frequency Division Multiple Access (FDMA). FDMA is used in the first generation analogue systems. The second generation cellular mobile systems, such as the European GSM standard and the USA's Interim Standard IS-54 [6] have one common feature – they use Time Division Multiple Access (TDMA) to enable simultaneous access of mobile users. Unlike FDMA, in a TDMA system each user accesses the whole of the assigned bandwidth, but only for a fraction of time and on a periodic basis.

Code Division Multiple Access (CDMA) is used in Interim Standard 95 and it is currently being standardized for Universal Mobile telecommunications System (UMTS)]. The CDMA technique assigns uncorrelated codes to the mobile users, thus enabling them to access the full bandwidth, and for the complete duration of the call. This feature gives CDMA the advantage over FDMA and TDMA schemes.

CDMA (Direct Sequence Code Division Multiple Access) is considered as the third generation of cellular mobile, indoor wireless and personal communication systems. CDMA offers attractive features, such as frequency reuse, soft handoff, increased capacity and multipath combating.

In a CDMA system, a communication channel with a given bandwidth is accessed by all the users simultaneously. The different mobile users are distinguished at the base station receiver by the unique spreading code assigned to the users to modulate their signals. Hence, the CDMA signal transmitted by any given user consists of that user's data which modulates the unique spreading code assigned to that user which in turn modulates a carrier (the frequency of which is the same for all users), using any well-known modulation scheme such as binary phase shift keying (BPSK). Figure 1 shows the modulation of the bits of the users by a spreading code[4].

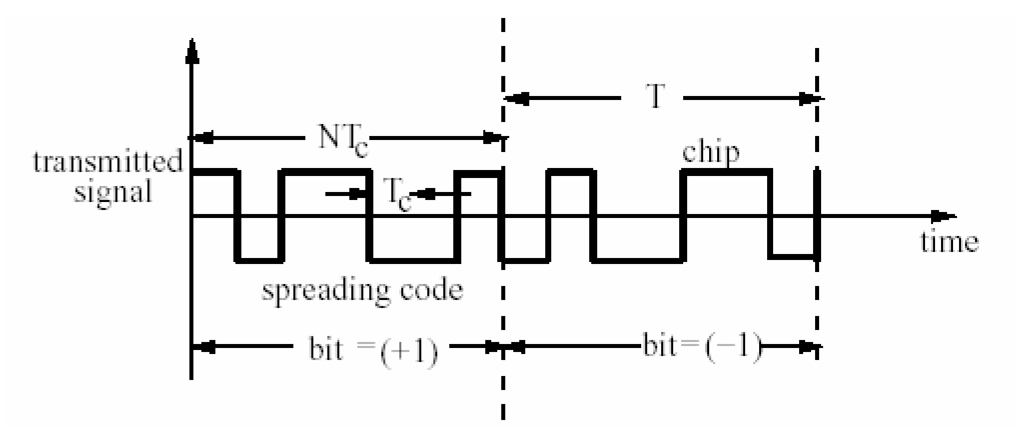

FIGURE 1: Spreading in a direct sequence CDMA system. The transmitted signal consists of 2 bits +1 and -1. Each bit is multiplied by a spreading code f+1,-1,+1,+1,- 1,-1,+1g consisting of 7 chips. T is the bit period, Tc is the chip period, and N is the number of chips per bit.

The low cross-correlation between the spreading codes of various users and peaky auto-correlation property of each code provide the basis for detection of the transmitted symbols of each user at the receiver. Wireless systems involve two radio links: the reverse link or the uplink from the mobile to the base station, and the forward link or the downlink from the base station to the mobile. Gold code generators are used extensively in Code Division Multiple Access . The Gold code generators use efficiently implemented Linear Feedback Shift Registers In a multi-user CDMA system several forms of "Spread Spectrum" modulation techniques are used. The most popular is the Direct Sequence Spread Spectrum (DS-SS). In this form of modulation each user signal is uniquely coded and spread across a wide band of transmission frequencies. Pseudo-random Noise (PN) sequences that are orthogonal to each other are used to code the user signals. Two sequences are considered orthogonal when their cross correlation coefficient is zero[4].

The first aim is to calculate the bit error rate of the linear detector like matched filter bank, MMSE detector, LMS detector. Then to determine the SNR for non linear detector using the neural network. Here multilayer perceptron is used by using the back propagation algorithm. It shows the better bit error rate performance for the nonlinear detector than the linear one but it has been seen when the no of user's increases linear detector shows the poor performance.

In a CDMA system, several users simultaneously transmit information over a common channel using preassigned codes. The conventional single user detector consists of a bank of filters matched to the spreading codes and then deciding on the sign of the outputs. This detector suffers from two problems. First, Multiple Access Interference (MAI) produced by the other co-channel users is a significant limitation to the capacity of this detector. The second problem is the near-far effect, which occurs when the relative received power of interfering signals becomes larger.

A potential solution is multi-user detection ,which exploits the information of the signals of interfering users. The optimum multi-user detector evaluates a log-likelihood function over the set of all possible information sequences. It achieves low error probability at the expense of high computational complexity, which increases exponentially with the number of users. So this method is extremely complex for a realistic number of users. Consequently, there has been considerable research into suboptimal detectors. These detectors achieve significant performance gains over the conventional detector without the exponential increase in receiver complexity. Several factors motivate us to apply Neural Networks (NN) as multi-user detectors[11]. They are adaptive and computationally efficient. Also, the cyclostationary structure of MAI and nonlinear decision boundaries formed by an optimal receiver in CDMA can be estimated by NN Aazhang et al. first reported a study of a multilayer perceptron NN in CDMA systems, and showed that in the case of applying a complicated algorithm named assisted BP, in which the number of hidden layer nodes grows exponentially with the number of users, its performance is close to that of the optimum receiver in both synchronous and asynchronous Gaussian channels.

2. THE SYSTEM MODEL OF CDMA :

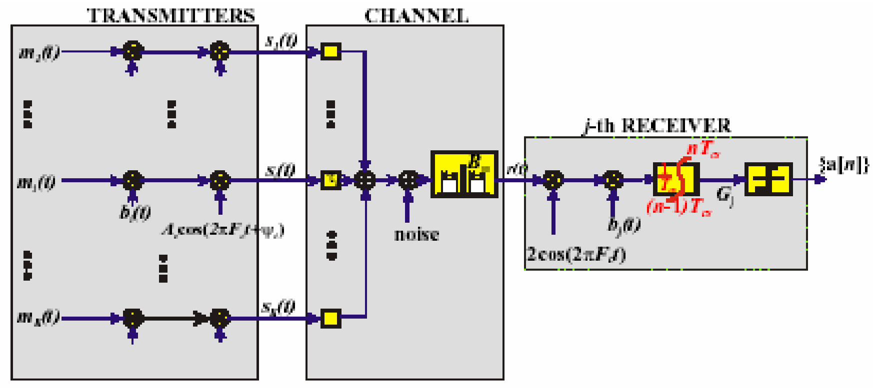

FIGURE 2: TRANSMITTER MODEL

The system model consists of K independent simultaneous users. The kth user's transmitted signal assuming BPSK data modulation is of the form.

$$Y_k(t) = \sum_k \sqrt{E_k(i)} b_k(i) s_k(t - iT) \tag{1}$$

Where $E_k(i)$ is the power of the kth user at time iT,1/T is the data rate, $b_k\ \varepsilon$ {±1} is the data bit of user k during the ith interval, and s_k (t) is the spreading (signature) waveform of duration T and normalized power which is composed of a spreading sequence of N chips (code length) as

$$s_k(t) = \sum_{n=0}^{N-1} a^k{}_n(t)\, p(t - nT_c) \tag{2}$$

Where $a^k{}_n\ \varepsilon$ (-1, 1) is the spreading sequence, p(t) is the rectangular waveform of duration T_c, and T = nT_c. We obtain the receiver input and output in AWGN and fading Channels.

3. MULTIUSER-DETECTION

Multiuser detection is a technology that spawned in the early 80's. It has now developed into an important, full-fledged field in multi-access communications. Multiuser Detection (MUD) is the intelligent estimation/demodulation of transmitted bits in the presence of Multiple Access Interference (MAI). MAI occurs in multi-access communication systems (CDMA/ TDMA/ FDMA) where simultaneously occurring digital streams of information interfere with each other. Conventional detectors based on the matched filter just treat the MAI as additive white gaussian noise (AWGN).However, unlike AWGN, MAI has a nice correlative structure that is quantified by the cross-correlation matrix of the signature sequences. Hence, detectors that take into account this correlation would perform better than the conventional matched filter-bank. MUD is basically the design of signal processing algorithms that run in the black box shown in figure These algorithms take into account the correlative structure of the MAI.

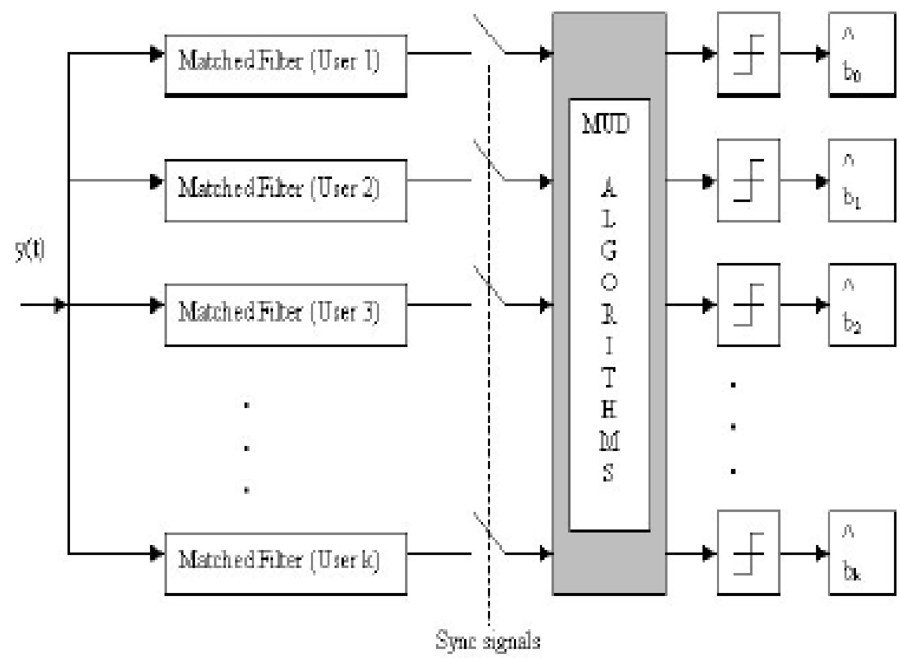

FIGURE 3.1: A matched filter bank

The decision statistic a the output of the Kth matched filter is given by

$$y_k = \int_0^T y(t) s_k(t) dt \tag{3}$$

where y(t) and sk(t) is given by (1) and (2). Expanding the above equation

$$y_k = \int_0^T \{\sum_{j=1}^{K} A_j b_j s_j(t) + n(t)\} s_k(t) dt \tag{4}$$

Using eq(3)

$$y_k = \sum_{j=1}^{k} A_j b_j \rho_{jk} + n_k \tag{5}$$

$$n_k = \int_0^T n(t) s_k(t) dt \tag{6}$$

Where $\rho_{11} = 1$ and y simplifies to

$$y_k = A_k b_k + \sum_{j=1, j \neq k}^{K} A_j B_j \rho_{jk} + n_k \tag{7}$$

The 2nd term in the above eq is the MAI. The matched filter treats the MAI just as white noise. The noise variance at the output of the matched filter is given by

$$E(n_k^{\ 2}) = E[\int_0^T n(t)s_k(t)dt \int_0^T n(s)s_k(s)ds] = \int_0^T\int_0^T E[n(t)n(s)]s_k(s)s_k(t)dtds$$
$$= \int_0^T\int_0^T N_o\delta(t-s)s_k(t)dtds = \int_0^T N_o s_k^{\ 2}(t)dt = N_o \quad (8)$$

Similarly, the noise covariance can be shown to be

$$E(n_i n_j) = N_0\rho_{ij} \quad (9)$$

Hence the noise covariance matrix can be defined as

$$E[nn^T] = \{N_0\rho_{ij}\} = N_0 R \quad (10)$$

where R is given by (4) and $n = [n_{1,}n_2......,n_k]^T$. Stacking up (2.5) for all the users we get

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_k \end{bmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1k} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{21k} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{k1} & \rho_{k2} & \cdots & \rho_{kk} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_k \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_k \end{bmatrix} \quad (11)$$

In matrix notation we have,

$$y = RAb + n \quad (12)$$

It is observed that as the MAI increases (the number of users increases) the performance becomes poor. This is because the detector ignores the cross-talk between users (the MAI) as white noise. Good MUDs, as described in the next few sections, take into the account the correlative property of the cross-talk.

3.1 Limitations of the conventional detector

Although {y1,y2,…,y_k} are sufficient statistics for detecting {b1,b2,…,b_k}, y_k is not a sufficient statistic for detecting bk. The conventional detector makes the mistake of making this assumption(y_k is a sufficient statistic for detecting bk) by ignoring the MAI as background noise. This is one reason for the poor performance of the matched filter bank when the number of users are large. Another serious limitation of the conventional detector is that it is seriously affected by the near-far problem.This causes a significance degradation in the system performance even when the number of users is very small. Adapting (3.9) to the 2 user scenario we get the fact that Q is a monotonically decreasing function was used to get the upper bound. If the interferer is not dominant , the bit error probability is less than half. But if the interferer is dominant (near-far problem) the bound becomes greater than half. Consider the case when there is no noise in the system and the interferer is dominant, Here we see that in the absence of noise, though highly hypothetical, the matched filter receiver reduces to flipping a coin and deciding the output bits. This is an undesirable feature of the conventional detector (may perform better in the presence of noise than in the absence of noise).

3.2 The MMSE Linear Detector

At low SNRs, the matched filter bank performs better than the decor relating detector as observed from figure 3.6. Hence, it might be possible to improve the performance by incorporating some SNR information in the MUD algorithms. In this section, one such approach is investigated where the mean squared error between the output and data is minimized. The detector resulting from

the MMSE (minimum mean square error) criterion is a linear detector[1]. Two different adaptive approaches of the MMSE linear detector are also studied at the end of this section. One of the approaches requires no prior information of the SNRs or the signature waveforms but requires a training sequence to adapt and compute the optimum weights to be applied on the received statistic. The other approach does not need a training sequence but requires exact knowledge of the signature sequence. Being a linear detector like the decor relating detector, the MMSE receiver also weights thereceived statistic y with a weight vector w to form the decision statistic[1]. It has been proved that minimizing the MSE at the output of the linear transformation is equivalent to maximizing the SIR at the output of the linear transformation. The optimal value of the minimizes the MSE between the weighted received statistic and the transmitted bit is derived in the next section. ..The receiver structure for user m is
shown in figure.

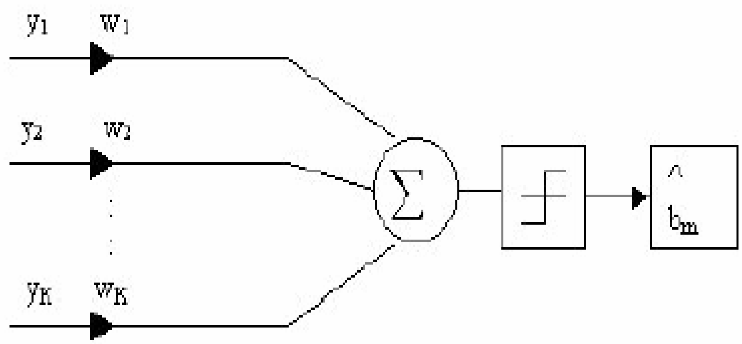

FIGURE 3.2: MMSE linear transformation for user m.

3.2.1 Optimal Weights for an MMSE Linear Detector in an AWGN Channel

The MMSE linear detector for user 1 determines a waveform c1(t) such that the MSE error between the transmitted bit and the correlation between c1(t) and the received signal y(t) is minimized. The objective function (the mean square error in this case) is defined as

$$\psi(c1) = E\left\{\left(b_1 - \langle c1, y \rangle\right)^2\right\} \qquad (13)$$

In the finite dimensional representation of the above eq can be expressed as

$$\psi(w_1, \quad w_2, \quad ..., \quad w_K) = E\left\{\left(b_1 - \sum_{i=1}^{K} w_i y_i\right)^2\right\} \qquad (14)$$

Where $\{w_1, w_2, \ldots, w_k\}$ are the weights operating on the received statistic $\{ y_1, y_2, \ldots, y_k\}$. Representing the above eq in a compact and convenient matrix notation,

$$\psi(w) = E\left\{\left(b_1 - w^T y\right)^2\right\}$$

Using linearity of the Expectation operator,

$$\psi(w) = E(b_1^{\ 2}) - E(2b_1 w^T y) + E\left\{\left(w^T y\right)\left(w^T y\right)^T\right\}$$

$$\psi(w) = 1 - 2w^T E(b_1 y) + E\left\{w^T y y^T w\right\} \qquad (15)$$

Since the bits of user 1$E(b_1^{\ 2})=1$, Therefore,

$$\psi(w) = 1 - 2w^T E(b_1 y) + w^T E\left\{ y y^T \right\} w \qquad (16)$$

From eq 15, we have

$$y = RAb + n$$

Consider, $E(b_1 y) = E(b_1 RAb + b_1 n)$

$$= RAE\left(b_1 \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix} \right) + E(b_1 n)$$

$$= RA \begin{bmatrix} E(b_1^{\ 2}) \\ E(b_1 b_2) \\ \vdots \\ E(b_1 b_K) \end{bmatrix} + b_1 E(n) \tag{17}$$

Since the bits of user 1 are uncorrelated with the bits of other users we have,

$$E(b_1 b_K) = \begin{cases} 0 & , i \neq j \\ 1 & , i = j \end{cases} \tag{18}$$

Using eq 17 and the fact that the noise n is zero mean i.e., E(n)=0 in 3.26

$$E(b_1 y) = RA[1 \quad 0 \quad \cdots \quad 0]^T \tag{19}$$

Using the definition of A and R

$$E(b_1 y) = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_K \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\therefore E(b_1 y) = \begin{bmatrix} \rho_{11} A_1 \\ \rho_{21} A_1 \\ \vdots \\ \rho_{K1} A_1 \end{bmatrix} \tag{20}$$

Now consider the second expectation term in eq 3.22

$$E\{yy^T\} = E\{(RAb)(RAb)^T\} + E(nn^T)$$
$$= E\{RAbb^T A^T R^T\} + N_o R \tag{21}$$

Using the fact that A and R are symmetric matrices, we get

$$E\{yy^T\} = RAE\{bb^T\}AR + N_o R$$
$$= RA^2 R + N_o R \tag{22}$$

Substituting eq 20and eq 22 in eq 15

$$\psi(w) = 1 - 2w^T \left[\rho_{11}A_1 \quad \rho_{21}A_1 \quad \cdots \quad \rho_{K1}A\right]^T + w^T(RA^2R + N_oR)w \tag{23}$$

The above equation gives the objective function (MSE) that should be minimized according to the MMSE criterion. Performing a matrix derivative operation on (14) we get,

$$W_{opt} = (R + N_0A^{-2})^{-1} \tag{24}$$

Where $$N_0A^{-2} = diag\left\{\frac{N_0}{A_1^{\ 2}}, \quad \frac{N_0}{A_2^{\ 2}}, \quad \cdots, \quad \frac{N_0}{A^2_{\ k}}\right\} \tag{25}$$

The MMSE detector requires the SNR information and hence again precomputation of the matrix inverse is not a feasible solution. Also, getting good estimates of the SNR is not temporally efficient. Therefore, it would be nice if there was some way to eliminate the need to compute matrix inverses and the need to have apriori information (signature sequences) and other additional information (SNR) for decoding. This objective can be realized through adaptive MUD algorithms. Adaptive algorithms “learn” the desired filter response from the received signals. There are different approaches to implement the “learning” capability.Two approaches will be studied in the next sub- calls for a training sequence.The second approach doesn’t require any training sequence but requires exact knowledge of the signature sequences of the users and also takes longer to converge.

3.3 system model(neural network)

The optimum multi-user detector evaluates a log-likelihood function over the set of all possible information sequences. It achieves low error probability at the expense of high computational complexity that increases exponentially with the rule for multi-user detection of DS/CDMA[7-9] signals in AWGN(Additive White Gaussian Noise) and multipath fading channels The results show superior improvement over the previous studies in terms of the receiver complexity .

Therefore, this method is extremely complex for a realistic number of users. Consequently, there has been considerable research into suboptimal detectors. These detectors achieve significant performance gains over the conventional detector without the exponential increase in the receiver complexity. In this section, we explain multilayer perceptron and Hopfield neural networks. We first describe the back propagation (BP) algorithm for training multilayer perceptron. Since our goal is to improve the performance of BP neural network, subsequently we explain different training algorithms and criterion that have shown better performance than the BP in radar, sonar, speech, and pattern recognition applications. Then Hopfield neural network is explained.

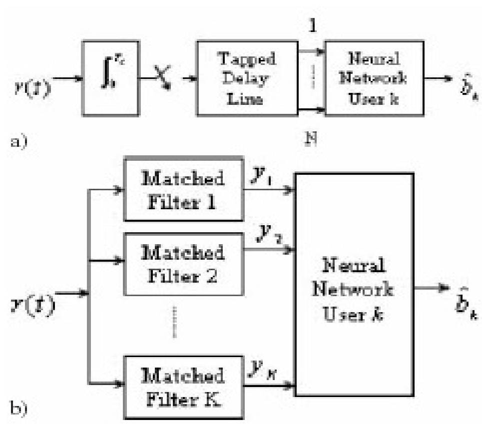

FIGURE 3.2: Two kinds of processing of the received signal.

In this section, we explain multilayer perceptron and Hopfield neural networks. We first describe the back propagation (BP) algorithm for training multilayer perceptron.

Since our goal is to improve the performance of BP neural network, subsequently we explain different training algorithms and criterion that have shown better performance than the BP in radar, sonar, speech, and pattern recognition applications. Then Hopfield neural network is explained. In this section, we explain multilayer perceptron and Hopfield neural networks. We first describe the back propagation (BP) algorithm for training multilayer perceptron. Since our goal is to improve the performance of BP neural network, subsequently we explain different training algorithms and criterion that have shown better performance than the BP in radar, sonar, speech, and pattern recognition applications. Then Hopfield neural network is explained.

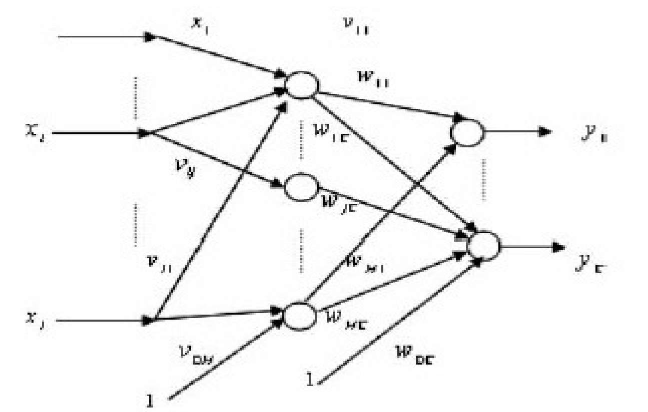

FIGURE 3.3: The structure of a typical two-layer perceptron neural network

Multilayer perceptron is a feed forward network where the outputs of each layer are applied to the inputs of the next layer. Figure 1 shows the structure of a typical
two-layer perceptron neural network containing one hidden layer and output layer. The parameters of network are defined as:

- The numbers of nodes in the input, hidden, and output layers are I, H, and C, respectively.
  - x_i: the ith input unit.
  - v_{ij}: weight between the ith input unit and the jth unit of hidden layer.
  - v_{0j} : bias weight;
  - w_{jk}: weight between the jth unit of hidden layer and the kth output;
  - w_{ok}: bias weight;
  - z_{inj}: the jth input unit of hidden layer;
  - z_k: thejth output of hidden layer;
  - y_{ink}: thekth input of output layer;

  y_k: the kth unit of output

$$zin_j = \sum_{i=1}^{I} x_i v_{ij} + v_{oj}$$

layer;

$$z_j = f(zin_j)$$

$$yin_k = \sum_{j=1}^{H} z_j w_{jk} + w_{ok}$$

$$y_k = f(yin_k)$$

- f(.): activation function;
- t_k: the desired output or target.

3.4 Minimum mean square error (back propagation) Criterion

In this common criterion, the objective of network training is to find the optimal weights to minimize the sum of square error between the desired outputs (targets) and actual outputs of net .

$$E = \frac{1}{2M}\sum_{m=1}^{M}\sum_{i=1}^{C}\left[t_i(m) - y_i(m)\right]^2 \tag{26}$$

Where M is the number of training patterns, C is the number of outputs, ti(m) is the ith component of the mth target (±1 in CDMA), and yi(m) is the ith output of the network for the mth input pattern. The weight updating is obtained according to the following rule:

$$W(new) = W(old) - \mu\frac{\partial E}{\partial W} \tag{27}$$

where W is the weights of the net (containing v and w) and µ is the learning rate. The weight change rules are as follows

$$\begin{cases} \Delta w_{jk} = \mu\delta_k z_j \\ \Delta w_{0k} = \mu\delta_k \quad \text{where} \quad \delta_j = \delta in_j f(zin_j) \end{cases} \tag{28}$$

$$\begin{cases} \delta v_{ij} = \mu\delta_k z_j \\ \delta v_{0j} = \mu\delta_j \quad \text{where} \quad \delta_j = \delta in_j f'(zin_j) \\ \delta in_j = \sum_{k=1}^{C}\delta_k w_{jk} \end{cases} \tag{29}$$

In CDMA application, we use bipolar sigmoid as activation function:

$$f(u) = \frac{1-e^{-u}}{1+e^{-u}} \Rightarrow f'(u) = (1-f(u))(1+f(u)) \tag{30}$$

Depending on the sign of the output of the network, the received signal will be classified to ±1. This network is approximation-based formulation net, i.e., aim is how close the result is to the expected value. In CDMA application, our goal is the classification of the received data, therefore it is only necessary to know the correctness of the classification. Hence we use decision based networks[12,13].

The first step is to feed the input vector through the network and compute every unit in the network. Recall that this is done by computing the weighting sum coming into the unit and then applying the sigmoid function. The second step is to compute the squared error of the network. Recall that this is done by taking the sum of the squared error of every unit in the output layer. The target vector involved is associated with the training sample (the input vector). The third step is to calculate the error term of each output unit, indicated below as 'delta'. The error term is related to the partial derivative of each weight with respect to the network error. The fourth step is to calculate the error term of each of the hidden units. The hidden unit error term depends on the error terms calculated for the output units. The fifth step is to compute the weight deltas. 'Eta' here is the learning rate. A low learning rate can ensure more stable convergence. A high learning rate can speed up convergence in some cases. The final step is to add the weight deltas to each of the weights. I prefer adjusting the weights one layer at a time. This method involves recomputing the network error before the next weight layer error terms are computed[8,10].

4. SIMULATION AND RESULT

Finally there is the simulation first done on the various nonlinear detector like matched filter bank, which is the conventional one consists of bank of filters. the simulation is done in order to get the better performance over the linear one like multilayer perceptron. Conventional detectors based on the matched filter just treat the MAI as Additive White Gaussian Noise (AWGN).Unlike MAI has a nice correlative structure that is quantified by the cross-correlation matrix of the signature sequences. Linear MUDs are detectors that operate linearly on the received signal statistics i.e they perform only linear transformations on the received statistics. Then analysis done on the MMSE detectors where the mean square error between the output and data is minimized. The detector resulting from the MMSE (Minimum Mean Square Error)criteria is a linear detector. It has been shown that minimizing the MSE at the output of the linear transformation is equivalent to maximizing the bit error rate the output of the linear transformation.

The first example of non linear detector is matched filter bank. This section introduces and analyses the matched filter bank detector which was the conventional and most simplest way of demodulating CDMA signals (or any other set of mutually interfering digital streams). In conventional single-user digital communication systems, the matched filter is used to generate sufficient statistics for signal detection. In the case of a multi-user system, the detector consists of a bank of matched filters (each matched to the signature waveforms of different users in the case of CDMA)[11,14]. This type of detector is referred to as the conventional detector in MUD literature.

It is observed that as the MAI increases (the number of users increases) the performance becomes poor. This is because the detector ignores the cross-talk between users (the MAI) as white noise. Serious limitation of the conventional detector is that it is Seriously affected by the near-far problem. This causes a significant degradation in the system performance even when the number of users is very small. It is observed that at low SNRs the matched filter performs better. Hence, the decorrelating detector is not an optimal.

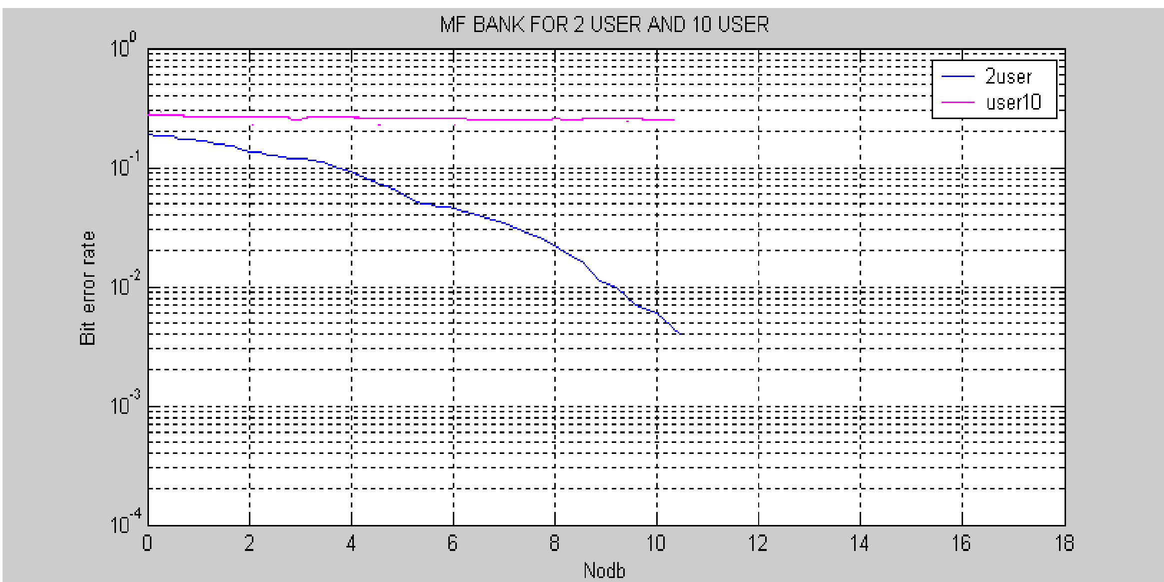

FIGURE4.1: Comparision of Matched filter bank of 2 user with 10 user

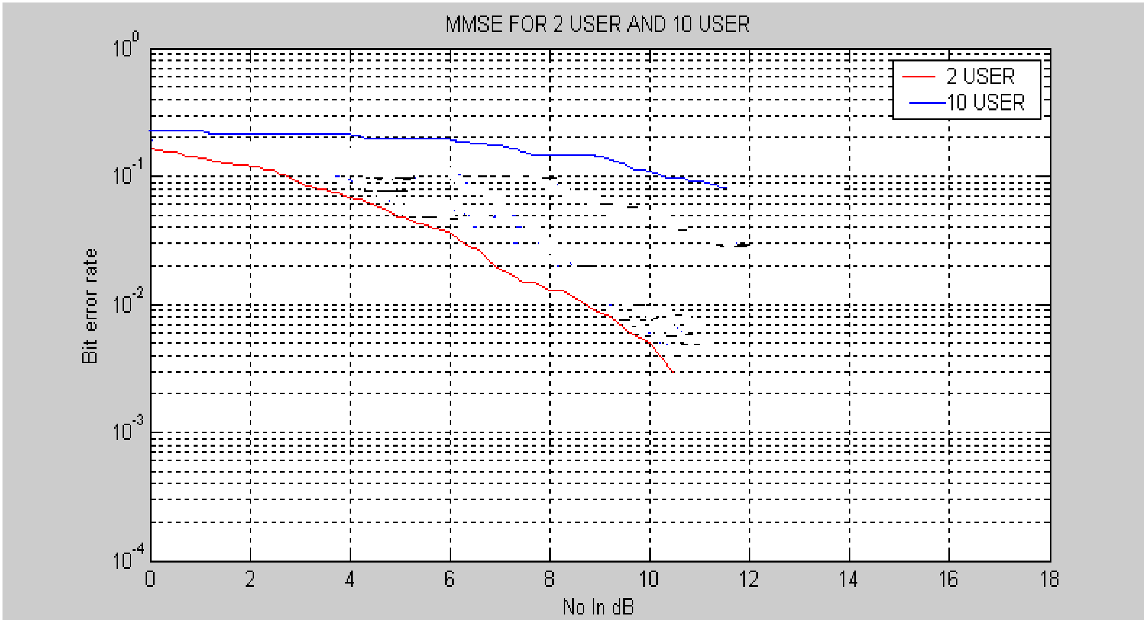

FIGURE4.2: Comparision of Matched filter bank of 2 user with 10 user

The second example of the linear detector is MMSE. At low SNRs, the matched filter bank performs better than the decorrelating detector as observed from figure. Hence, it might be possible to improve the performance by incorporating some SNR information in the MUD algorithms. In this section, one such approach is investigated where the mean squared error between the output and data is minimized. The detector resulting from the MMSE (minimum mean square error) criterion is a linear detector.

Two different adaptive approaches of the MMSE linear detector are also studied at the end of this section. One of the approaches requires no prior information of the SNRs or the signature waveforms but requires a training sequence to adapt and compute the optimum weights to be applied on the received statistic. The other approach does not need a training sequence but requires exact knowledge of the signature sequence. It has been proved that minimizing the MSE at the output of the linear transformation is equivalent to maximizing the SIR at the output of the linear transformation that the MMSE receiver maximizes the SIR at the output of the transformation shown in the above figure.

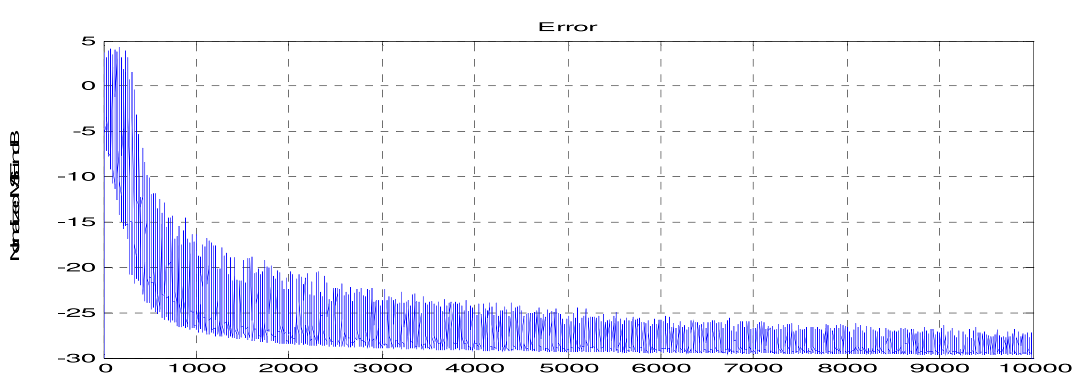

FIGURE4.3: Training curve for MLP for different samples .

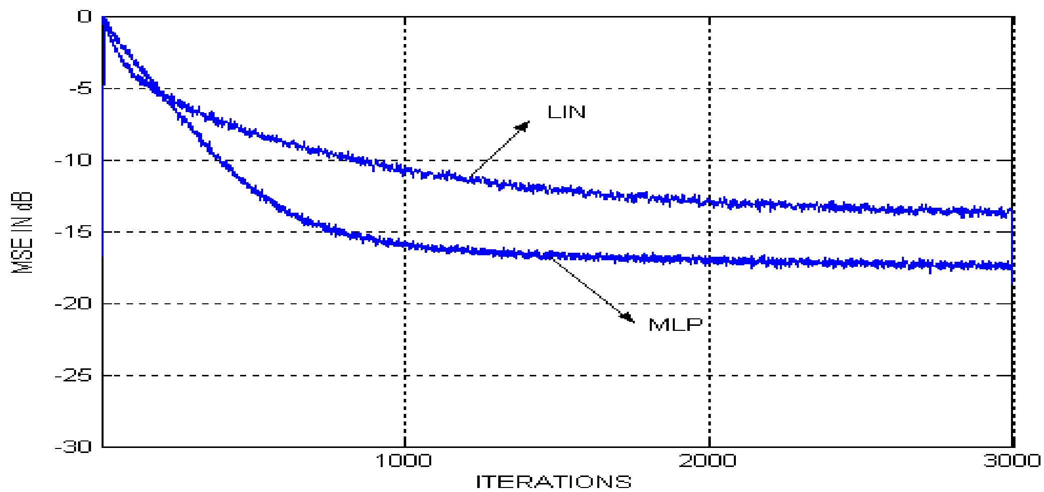

FIGURE4.4: Comparison of learning for linear and nonlinear detectors.

5. CONCLUSION AND FUTURE WORK

This thesis review gives a background on the fundamental concepts of linear and nonlinear detector. Different detectors like matched filter bank, MMSE detectors, and LMS detectors were studied. Further MLP based detector is suggested for CDMA detection which provides improvement in BER performance over the nonlinear one. For multi-user detection problem this Neural Network based detector[16] also has reduced structural configuration which helps for easier real time implementation. Faster learning using BP algorithm and with less no of training samples show that there is scope for its use in practical detectors.

Estimating the performance of linear and non linear detector has greater importance. Here the back propagation algorithm is proposed. Which provides better performance curve and training than the linear one. Instead of BP RLS can also be proposed which is having faster learning. Some aspects of the proposed algorithm are only briefly touched in this thesis and may be further investigated. The proposed algorithms are only for performance of ber which shows greater signal to noise ratio. The proposed algorithm for ber performance focused on only AWGN channel. It is proposed that the algorithm is to be further extended for fading channel signals since in fading channel shows better performance which is having greater importance as it involves multipath fading in it.

The performance of BP network[17,18] in AWGN channel with the conventional decorrelator multistage and optimum detectors widely used for comparative analysis. SVM (Support vector machine) also can be used as detectors. In fading channel the rake and single user lower bound receivers are considered for comparison. Since our goal is to improve the performance of BP net, we consider different neural networks.

We can apply decision based neural network (DBNN), fuzzy decision neural network (FDNN) discriminative learning, minimum classification. We also propose modified DBNN that outperforms DBNN. A comparison between BP perceptron and Hopfield neural nets can From the above results we can conclude that neural network can be used as multi-user detector in CDMA systems. Its performance depends on the parameters, where they are obtained by experiments. The number of training samples and hidden layer nodes and computational complexity increases with the number of users. The complexity of neural network is in the training phase that can be organized in parallel. Of course the hardware implementation of neural network especially for large number of users in a realistic environment should be considered.

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