HIGH PERFORMANCE NEURAL NETWORK BASED MULTIUSER DETECTOR IN CDMA

Sung H. Yoon and Sathyanarayan. S. Rao

Dept. of Electrical and Computer Engineering
Villanova University, Villanova, PA 19085
shyoon@sitar.ee.vill.edu

ABSTRACT

We present a high performance neural network based multiuser detector in code division multiple access (CDMA) communications. This detector retains salient features of the annealed neural network based detector (ANNMD) and reduces its computational complexity. The BER performance of the proposed detector is close to the theoretical lower bound of the BER performance. We present a theoretical derivation of the hybrid type multiuser detector with improved hardware complexity. Extensive numerical evaluation of the proposed techniques as well as various suboptimal multiuser detectors is conducted using Monte-Carlo simulation.

1. INTRODUCTION

The importance of wireless communication has increasingly been recognized in the military as well as the industrial community. Recently the code division multiple access (CDMA) technique has been developed based on the spread spectrum communication which has been used in military applications mainly for security purposes. The CDMA technique has become a strong candidate among existing techniques for wireless communication such as mobile communication, wireless local area network, etc.

In [1], we proposed an annealed neural network based multiuser detector (ANNMD) for white Gaussian CDMA channels. The architecture of ANNMD is equivalent to that of the Hopfield neural network based detector (HNN) [1,3]. Annealing the Hopfield neural network characterizes the ANNMD over the HNN. The ANNMD finds a near-global solution of the multiuser detection problem and exhibits performance close to that of the optimal multiuser detector (OMD).

The number of neurons in the ANNMD is linearly proportional to the number of users but computational complexity is still intensive compared to linear detectors [4]. We propose a hybrid type multiuser detector (HMD) to reduce the computational complexity of the ANNMD. The HMD consists of a linear detector as the front end followed by a back end nonlinear detector. By reducing the dimension of a signal vector through a front-end linear detector, we can reduce computational burden on the ANNMD which is nonlinear detector.

Contributions of this paper are: (1) Development of a new hybrid type multiuser detector which significantly reduces computational complexity of the ANNMD. (2) Extensive performance evaluation of the ANNMD and HMD which are superior to existing multiuser detectors [5].

2. A HYBRID MULTIUSER DETECTOR

2.1. Problem Formulation: Optimum Detection

We consider a synchronous CDMA white Gaussian channel shared by K users as shown in Fig. 1. Suppose that the kth user is assigned a pseudo-random signature waveform, $\{s_k(t), t \in [0, T_s]\}$, and that the information sequence of each user is antipodally binary. Then the receiver observes

$$r(t) = \sum_{k=1}^{K} b_k(j) \cdot s_k(t - jT_s) + \sigma n(t),$$

$$t \in [jT_s, jT_s + T_s] \qquad (1)$$

where $n(t)$ is a realization of a unit spectral density white Gaussian process and $\{b_k(j) \in \{-1, 1\}\}$ is the kth user information sequence [4]. Assuming that all information sequences are equally likely, we restrict attention to a specific symbol interval in Eq. 1. It is easy to check that the likelihood function depends on the outputs of a bank of matched filters:

$$y_k = \int_0^{T_s} r(t) \cdot s_k(t)dt \qquad (2)$$

and therefore $y=(y_1,...,y_K)$ are sufficient statistics for demodulating $b=(b_1...,b_k)$. y is represented as:

$$y = Hb + n \qquad (3)$$

where H is the nonnegative definite matrix of cross correlations between the assigned waveforms:

$$H_{ij} = \int_0^{T_s} s_i(t) \cdot s_j(t)dt \qquad (4)$$

and n is a zero-mean Gaussian K-vector with covariance matrix equal to $\sigma^2 H$. The optimum multiuser detector (OMD) selects the most likely hypothesis $\hat{b} = (\hat{b}_1, ..., \hat{b}_K)$ given the observation, which corresponds to selecting the noise realization with minimum energy, i.e.,

$$\hat{b} \in \arg \max_{b \in \{-1, 1\}^K} 2y^T b - b^T H b \qquad (5)$$

As shown in Eq. 5, the multiuser detection problem is now formulated as a quadratic combinatorial optimization problem.

2.2. The Annealed Neural Network Based Detector

In this section, we briefly review the ANNMD. Refer to [1] for complete derivation of the ANNMD. The ANNMD can be explained in the context of the HNN. The Let the ith output state of neuron V_i have the range $-1 < V_i < 1$. The energy function of the HNN can be derived to be:

$$E = -\frac{1}{2}\sum_{i \neq j}\sum T_{ij}V_iV_j - \sum_i I_iV_i \qquad (6)$$

where T_{ij} is the synapse efficacy, and I_i is an external current. This energy function is the same as the log likelihood function for multi-user detection as shown in Eq. 5. To map the log likelihood function onto the energy function of the Hopfield neural network, T_{ij} is slightly modified so that a monotonic decrease of the energy function of the network be ensured [2]:

$$T_{ij} = H_{ij} - e_{ij} \qquad (7)$$

where e_{ij} is the ijth element of a diagonal matrix E with $e_{ii} = \int_0^{T_s} s_i^2 dt$. The ANNMD finds the stable points of states by slowly increasing a neural gain from the low value, then we can find the global solution or a near global solution of the network without restriction on initial conditions. Therefore, the ANNMD employs the Hopfield neural network as its

basic architecture and a controllable neural gain for annealing. By means of annealing, the ANNMD outperforms the HNN.

2.3. The Hybrid Multiuser Detector

Nonlinear detectors show superior performance over linear detectors. On the other hand, they are computationally intensive compared to the linear detectors. We propose a hybrid multiuser detector (HMD) whose overall diagram is depicted in Fig. 5. The objective of this scheme is to reduce the computational load on the ANNMD. The HMD consists of a linear detector in the front end and a back-end nonlinear detector. The HMD first determines stronger signals using a linear detector and then weaker signals are determined by a nonlinear detector. Details of the process are as follows.

At the first stage of process, a linear detector is used to obtain an initial estimate of the originally transmitted user signals. The output signals from the linear detector are then divided into two groups: a group of stronger user signals and a group of weaker user signals. Signal decisions are first made for the stronger signals which must have a low probability of error. Signal decisions are deferred for the weaker signals. Two different implementations are possible to divide signals into the two groups. One implementation is to fix the number of signals in each group. This approach is easy to implement in hardware. The other implementation, called the null zone detection scheme is to set a threshold to decide the two groups. In this case, signal decisions are made for the signals with values above a predetermined threshold T_{nz} as shown in Fig. 1. Signal decisions are deferred for the signals with values below the threshold (signals in the null zone). In this approach, the number of users in each group will vary depending on channel conditions and a threshold level.
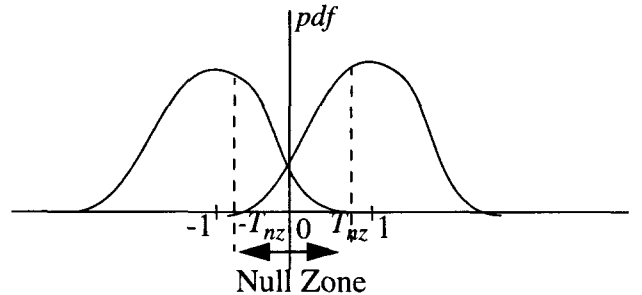

Fig. 1. The null zone in the *pdf* of an output from a linear detector

At the second stage, the outputs of the linear detector are rearranged and fed into a nonlinear detector as shown in Fig. 5. The likelihood function of the undetermined signals is formulated for optimal decision. Finally, we use a nonlinear detector to make the final decision for the undetermined signals. The number of inputs to the nonlinear detector can be controlled by adjusting the width of the null zone which affects the complexity of the nonlinear detector. The rearranged energy function with reduced number of users is established as follows:

$$E = 2y^T b - b^T H b \tag{8}$$

$$= 2 \cdot \begin{bmatrix} y_0 & y_1 \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} - \begin{bmatrix} b_0^T & b_1^T \end{bmatrix} \begin{bmatrix} h_{00} & h_{01} \\ h_{10} & h_{11} \end{bmatrix} \begin{bmatrix} b_0 \\ b_1 \end{bmatrix}$$

$$= (2 \cdot y_0 - b_1^T \cdot h_{10} - b_1^T \cdot h_{01}^T) \cdot b_0 - b_0^T h_{00} b_0$$

$$+ (2 y_1 b_1 - b_1^T h_{11} b_1) = 2 y_r^T b_0 - b_0^T h_{00} b_0 + C$$

where $b_0 = [b_0 \ b_1 \ ... \ b_n]$ indicates the undetermined users, $b_1 = [b_{n+1} \ ... \ b_K]$ indicates the determined users, $y_r^T = 2 \cdot y_0 - b_1^T \cdot h_{10} - b_1^T \cdot h_{01}^T$, and C is a constant. As shown in Eq. 8, the K-user detection problem is reduced to the n-user detection problem where $n \ll K$.

3. SIMULATION RESULTS

Extensive simulations are conducted to demonstrate the performance of the proposed multiuser detectors and compared with other suboptimal detectors. Representative existing multiuser detectors such as the conventional detector (CD), decorrelating-type detector (DEC), multistage detector (MSD), and the Hopfield neural network based detector (HNN) are tested.

3.1. BER Performance of the ANNMD

We consider modulated signals of five different users as being base band signals derived from Gold sequences of length seven [2]. We compared the CD, DEC, MSD, HNN, and ANNMD. The BER of the OMD was also evaluated to see the theoretical lower bound of the BER performance. The signal to noise ratio (SNR) of users 2-5 is fixed at 8 dB while the energy of the first user is varying. Fig. 2. depicts the error probabilities of the first user as a function of the

power ratio between the desired user and the rest of the users (interferences). The x-axis represents a decrease in the strength of the interfering signals relative to the first user's signal strength from left to right. The y-axis represents the BER of the first user among the five users. Therefore this example is a situation where the power of the desired user is stronger than others. In this case, the CD performs well over the MSD because the interfering energy is weaker than the user signal. As observed in the plot, the ANNMD shows a significant improvement of the BER performance over the tested suboptimal detectors and close to that of the OMD. The shape of the BER performance of the ANNMD follows that of the OMD which possesses the best near-far resistance. Note that the tested HHN was combined with the CD and it used the optimal network parameters suggested in [2] while our scheme was randomly initialized. Fig. 3. shows the results for the "near-far" situation where the power of the interferences is stronger than the power of the desired user. In this case, the CD shows the worst performance among the tested multiuser detectors due to the effect of the overwhelming power of the interferences. The ANNMD demonstrates the best performance among the suboptimal multiuser detectors in the severe near-far situation. Unlike the other suboptimal multiuser detectors which are vulnerable to the near-far problem, the ANNMD demonstrates its near-far immunity.

3.2. BER Performance of the HMD

Fig. 4. shows simulation results of the hybrid scheme. The y-axis in the figure represents an average of BERs over five users. HMD_H^{-1} and HMD_CD represent a hybrid scheme with the decorrelater and with the CD, respectively. In this simulation, the two strongest users were determined in the first stage and the remaining three users were computed in the second stage. As shown in the figure, the hybrid types provide better BER performances over existing suboptimal detectors.

4. CONCLUSIONS

In this paper, we presented an annealed neural network based multiuser detectors for a Gaussian CDMA channel. Unlike the HHN based approach, both the ANNMD and HMD do not require initial estimates and optimal parameter selection for the neural networks. It was shown from numerical simulations that the ANNMD and HMD provides significantly better BER performance than existing multiuser detectors.

5. REFERENCES

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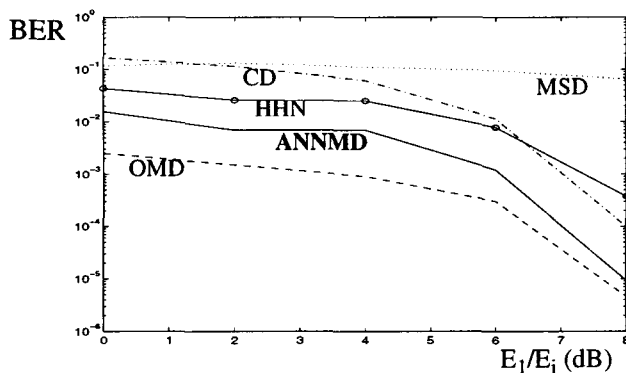
Fig. 2. Performance evaluation for the five user case; BERs of the CD, MSD, ANNMD, and OMD
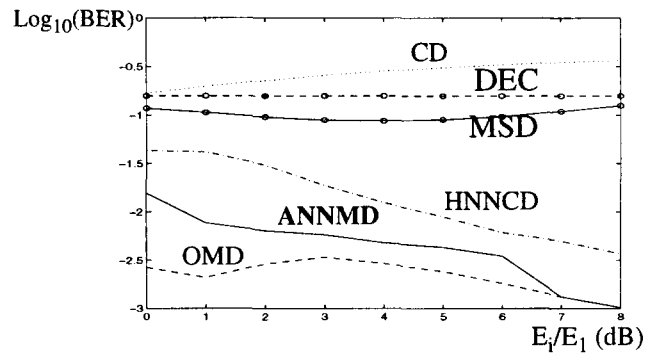

Fig. 3. Performance evaluation for the five user case; BERs of the CD, MSD, DEC, ANNMD
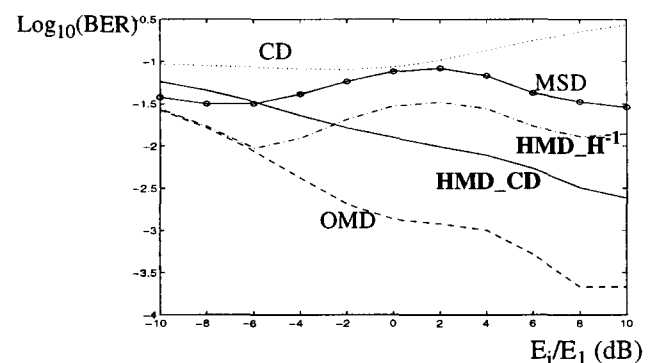

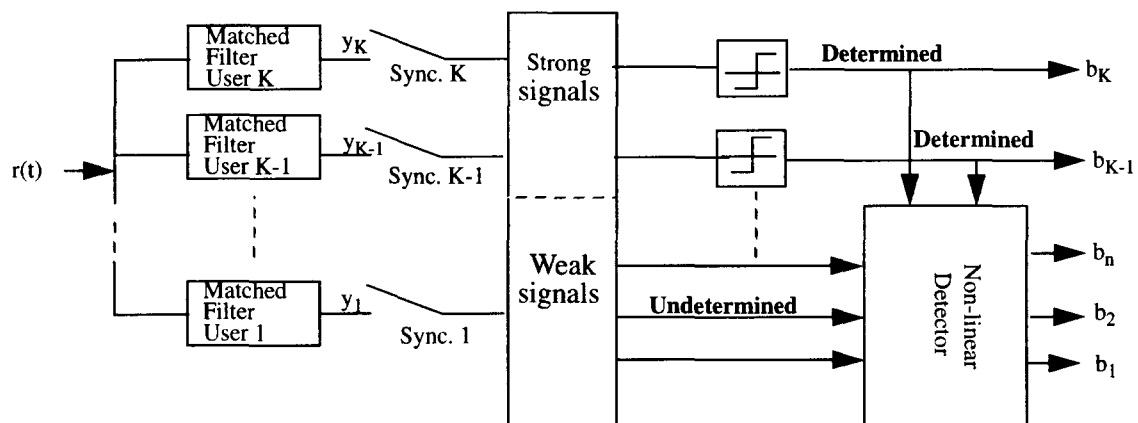Fig. 4. Performance evaluation for the five user case; averages of five user BERs

Fig. 5. A block diagram of the hybrid multiuser detector (CD + a nonlinear detector)