A NEW ADAPTIVE NEURAL NETWORK MULTIUSER DETECTOR IN SYNCHRONOUS CDMA SYSTEMS

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ABSTRACT

A new adaptive neural network multiuser detector is proposed and investigated for synchronous code-division multiple-access (CDMA) systems. The proposed multiuser detector includes two parts: a decorrelating detector as its auxiliary detector and an adaptive multiple layer perceptron (MLP) detector as its main detector. At the setup stage, the auxiliary detector detects the user's transmitted data and at the same time feeds these output data to the main MLP detector as its training data, and the main detector is trained by using the well-known backpropagation (BP) algorithm. After the training process, the auxiliary detector stops work and the main detector starts detecting the user's transmitted data self-adaptively. The proposed detector is blind and can provide near minimum bit-error-rate performance.

1. INTRODUCTION

Code-division multiple-access(CDMA) is an emerging technology. The traditional approach to demodulating spread-spectrum signal in CDMA comunication system is that the spread apectrum signal passes through a match filter, and a decision is made directly. As this method ignores the existance of multiple-access interferences, it is free of error only when a single user is transmitting information. As the levels of interference signals increase, the performance will be seriously degraded. Therefore some effective multiuser detectors, such as decorrelating detector (decorrelator), multi-stage detector, decorrelating decision feedback detector, adaptive detector, and neural network detector, have been proposed and investigated in [1-6]. The neural network multiuser detectors are considered In [2,3,5,6], and are shown to achieve near-optimum multiuser detection performance. However, the system correlation matrix and the users' energy matrix must be known in advance. In mobile CDMA systems, the users' energy matrix is time-varying and is not easy to be estimated accurately. We proposed in [4] and [5] a backpropagation neural network multiuser detector in which a prior knowledgment of the user's energy matrix is not necessary and close to minimum bit-error-rate performance can still be achieved. However, similar to other adaptive multiuser detectors, it requires a sufficiently long training code sequence in its training process. This could be difficult or even impossible in practical use. In order to overcome the weakness mentioned above, we propose in this paper an adaptive multiple layer perceptron (MLP) multiuser detector called A-MLP detector, by including a decorrelator as its auxiliary detector to extract a 'training' code sequence directly from the received signal. This approach can provide higher transmission efficiency and near minimum bit-error-rate performance.

2. CDMA MODEL AND MULTIUSER RECEIVERS

In a synchronous CDMA system with K users and a set of pressigned normalized waveforms $s_k(t)$ where $t \in [0,T]$ and $k = 1,2,...K$, the receiver observes

$$r(t) = \sum_{k=1}^{K} \sqrt{W_k} b_k(j) s_k(t - jT) + n(t), t \in [jT, jT + T] \tag{1}$$

where T stands for time duration of each information symbol; $n(t)$ is a white Gaussian noise process with variance σ^2; $b_k(j)$ is the j-th symbol of the k-th user's information sequence, taking -1 or $+1$ only; and W_k is the received k -th user's signal energy. After $r(t)$ passes a bank of matched filters which matches to each user's signature waveform $s_k(t)$, its sampled outputs at

$t = jT$ are as follows:

$$y_k(j) = \int_{(j-1)T}^{jT} r(t)s_k(t - jT)\,dt, k = 1, 2, ..., K \quad (2)$$

and therefore $\mathbf{y}(j) = (y_1(j), y_2(j), ..., y_K(j))^T$ are sufficient statistics for demodulating $\mathbf{b}(j) = (b_1(j), b_2(j), ..., b_K(j))^T$. Substituting (1) into (2), we get

$$\mathbf{y}(j) = \mathbf{RWb}(j) + \mathbf{z}(j) = \mathbf{Hb}(j) + \mathbf{z}(j) \quad (3)$$

where $\mathbf{R}$ is a $K \times K$ positive definite matrix of signature waveform cross-correlations with its elements

$$r_{ij} = \int_0^T s_i(t)s_j(t)\,dt \quad (4)$$

and $\mathbf{W}$ is a diagonal matrix with its diagonal elements equal to $\sqrt{W_k}, k = 1, 2, \ldots, K$, and $\mathbf{H} = \mathbf{RW}$ is the system transfer matrix. The term $\mathbf{z}(j)$ is a Gaussian noise vector with the $K \times K$ cross-correlation matrix $\mathbf{R}(\mathbf{z}) = \sigma^2\mathbf{R}$. The objective of a multiuser detector is to recover the input data vector $\mathbf{b}(j)$ given the output vector $\mathbf{y}(j)$.

Conventional single-user detector is the simplest way to make decisions based on $y_k(j)$, demodulation is decoupled and the multiuser interference is ignored, yielding the following decisions for the k-th user:

$$\hat{b}_k(j) = sgn(y_k(j)) \quad (5)$$

Thus, the probability P^I_{ek} that the k-th input is recovered incorrectly is

$$P^I_{ek} = 2^{1-K} \sum_{\mathbf{b}\in\{-1,1\}^K, b_k=-1} Q\left(\frac{W_k - \sum_{i=1, i\neq k}^K b_i H_{ik}}{\sigma\sqrt{W_k}}\right) \quad (6)$$

where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-\frac{y^2}{2}}\,dy$, and H_{ik} is the (i, k)-th element of the system transfer matrix H.

The linear decorrelating detector (decorrelator) obtains its output vector $\hat{\mathbf{b}}(j)$ by applying matrix filter $\mathbf{R}^{-1}$ followed by a set of decision devices (sign detectors) to $\mathbf{y}(j)$, which can be expressed as

$$\hat{\mathbf{b}}(j) = sgn(\mathbf{R}^{-1}\mathbf{y}(j)) \quad (7)$$

Thus, the probability P^{II}_{ek} that the k-th input is recovered incorrectly is:

$$P^{II}_{ek} = Q\left(\sqrt{\frac{W_k}{\sigma^2(\mathbf{R}^{-1})_{k,k}}}\right), k = 1, \ldots, K \quad (8)$$

where $(\mathbf{R}^{-1})_{k,k}$ stands for the (k, k)-th element of the inverse matrix of $\mathbf{R}$.

The optimum multiuser detector (OMD) obtains its detection output by selecting the most likely hypothesis $\hat{\mathbf{b}}^*(j) = [\hat{b}_1^*(j), \hat{b}_2^*(j), \ldots, \hat{b}_K^*(j)]^T$ given the observations $\mathbf{y}(j)$, which corresponds to selecting the noise realization with minimum energy , i.e.,

$$\hat{\mathbf{b}}^*(j) = arg \min_{\mathbf{b}(j)\in\{-1,+1\}^K} \mathbf{b}(j)^T\mathbf{Hb}(j) - 2\mathbf{y}(j)^T\mathbf{b}(j) \quad (9)$$

Therefore, OMD essentially decides and estimates each user's transmitted data $\mathbf{b}^*(j) = [b_1^*(j)b_2^*(j)\ldots b_K^*(j)]^T$ from the complete statistics $\mathbf{y}(j) = [y_1(j)y_2(j)\ldots y_K(j)]^T$ by the minimum error probability at time jT_b. Consequently, the optimum multiuser detection is a problem of decision and classification. When any user-transmitted data $b_k^*(j)$ is detected, the optimum decision function $f_{de}^{(k)}(\mathbf{y}(j))$ has the following form:

$$f_{de}^{(k)}(\mathbf{y}(j)) = \sum_{i=1}^{2^{(K-1)}} \left(e^{-\frac{1}{2\sigma^2}(\mathbf{y}(j)-\mathbf{y}_{+i}^{*(k)})^T\mathbf{R}^{-1}(\mathbf{y}(j)-\mathbf{y}_{+i}^{*(k)})} - e^{-\frac{1}{2\sigma^2}(\mathbf{y}(j)-\mathbf{y}_{-i}^{*(k)})^T\mathbf{R}^{-1}(\mathbf{y}(j)-\mathbf{y}_{-i}^{*(k)})}\right) \quad (10)$$

$$b_k^*(j) = sgn(f_{de}^{(k)}(\mathbf{y}(j))), k = 1, 2, \ldots, K \quad (11)$$

where

$$\mathbf{y}_{+i}^{*(k)} = \mathbf{Hb}_{+i} = \mathbf{RWb}_{+i}, i = 1, 2, \ldots, 2^{(K-1)} \quad (12)$$

$$\mathbf{y}_{-i}^{*(k)} = \mathbf{Hb}_{-i} = \mathbf{RWb}_{-i}, i = 1, 2, \ldots, 2^{(K-1)} \quad (13)$$

are called '+' and '-' non-noise complete statistic vectors when the k-th user transmits data bit $b_k(j) = +1$ and $b_k(j) = -1$, respectively. These vectors are determined only by matrix $\mathbf{H}$, i.e., matrices $\mathbf{R}$ and $\mathbf{W}$. Therefore the optimum decision functions are dependent upon three system parameters: energy matrix $\mathbf{W}$, correlation matrix $\mathbf{R}$, and channel noise variance σ^2. Now the optimum multiuser detection problem is changed into such a problem : how to implement the nonlinear optimum decision function $f_{de}^{(k)}(\mathbf{y}(j))$.

In [4] and [5], we used multiple layer perceptron (MLP), a feedforward neural network, to implement the nonlinear optimum decision functions, by learning through the well-known backpropagation (BP) algorithm. The advantages are that MLP can implement an arbitrary nonlinear decision function and therefore can achieve the minimum bit error rate performance, and also can track the slow change of the system parameters, say energy matrix $\mathbf{W}$, caused by the mobility of users. However there exists such a shortcoming that it requires very long training sequence before transmitting information bits, and have to be overcomed from the views of both practical applications and bandwidth efficiency.

In what follows, we will discuss a new adaptive multiuser detector which has all the advantages mentioned above but does not have that shortcoming.

3. STRUCTURE OF A-MLP MULTIUSER DETECTOR

As we know, the decorrelator is a good multiuser detector because it is optimum in near-far resistance and outperforms the convertional detector. So, it can be thought that the detection output of the decorrelator is nearly the same as the users' transmitted data and therefore can be used as the training data to the MLP. After its convergence, MLP is adapted self-adaptively not by the detection of the decorrelator but by the decision output of itself. In this way MLP can automatically track any changes of the channel parameters, such as energy matrix'chnages caused by the mobility of users, only if the changes are not too fast.

Based on the above idea, we propose in Figure 1 a new blind (self adaptive) multiuser detector called adaptive multiple layer perceptron (A-MLP) multiuser detector, where the multiuser detector consists of two parts: an auxiliary detector and a main detector The auxiliary detector uses a decorrelator because of its strong near-far resistant ability mentioned above, and the main detector uses a three layer MLP neural network with K neurons at the input layer, M neurons at the hidden layer, and one neuron at the output layer, because it can be adaptive and achieve close to minimum bit-error-rate performance [4]. At the set-up stage, the switch is set to $\hat{b}_{Ak}(j)$, the auxiliary detector is activated and the k-th user's data transmitted at time jT can be recovered as $\hat{b}_k(j)$. At the same time $\hat{b}_k(j)$ is feedback to train the MLP neural network. After the neural network has been trained, the switch will be set to $\hat{b}_{Mk}(j)$, the MLP detector will be activated and the corresponding k-th user's transmitted data $\hat{b}_k(j)$ will be recovered by the MLP detector.

4. ALGORITHMS OF A-MLP MULTIUSER DETECTOR

Well-known backpropagation (BP) algorithm is used in our A-MLP multiuser detector. The detailed adaptive learning and tracking algorithms are summarized as follows.

a) Initialize w, Δw, β, γ, and η
where $\mathbf{w}$ is the vector composed of all the neural network parameters, that is, $\mathbf{w} = [w_{ik}, w_i, \theta_i, \theta_0]^T$, where $\mathbf{w}_{ik}$ and $\mathbf{w}_i$ are the weights between input layer and the hidden layer and between the hidden layer and the output layer respectively and θ_i and θ_0 are the thresholds of the hidden neurons and the output neuron respectively; $\Delta\mathbf{w}(j) = \mathbf{w}(j) - \mathbf{w}(j-1)$ is the difference vector between $\mathbf{w}(j)$ and $\mathbf{w}(j-1)$; β and γ are momentum factor and learning rate, respectively; and η is a small predefined positive threshold.

b) Compute the output of the decorrelator

$$\hat{b}_{Aj}(i) = sgn([\mathbf{R}^{-1}]_i \mathbf{y}(j)) \tag{14}$$

where $[\mathbf{R}^{-1}]_i$ is the i-th row vector in the inverse matrix of the CDMA system correlation matrix $\mathbf{R}$, $\mathbf{y}(j) = [y_1(j)y_2(j)\dots y_K(j)]^T$ is the observation vector at j-th time interval and also the output vector of the matched filter bank and can be expressed as [1]

$$\mathbf{y}(j) = \mathbf{RWb}(j) + \mathbf{z}(j) \tag{15}$$

c) Compute the output of the neural network

$$g_k(j) = f_s(\sum_{i=1}^{M}(w_i f_s(\sum_{i=1}^{K} w_{ki} y_i(j) + \theta_i) + \theta_0) \tag{16}$$

$$\hat{b}_{Mk}(j) = sgn(g_k(j)) \tag{17}$$

where $f_s(.)$ is a sigmoid function and defined as $f_s(x) = (1-e^{-x})/(1+e^{-x})$.
Note that the output of the A-MLP detector has two different choices when working at different mode:

$$\hat{b}_k(j) = \begin{cases} \hat{b}_{Ak}(j) & \text{, when in learning mode} \\ \hat{b}_{Mk}(j) & \text{, when in tracking mode} \end{cases} \tag{18}$$

In the learning mode, when

$$(\sum_{l=0}^{L-1} \mid \Delta\mathbf{w}(j-l) \mid)/L < \eta \tag{19}$$

is achieved, the mode will be changed to the tracking mode, where L is the length of averaging .

d) Compute the error signal

$$e_k(j) = \hat{b}_k(j) - g_k(j) \tag{20}$$

e) Update the parameters of the neural network

$$\Delta\mathbf{w}(j) = \gamma\Delta\mathbf{w}(j-1) + \beta(-\nabla_{\mathbf{w}}(e_k(j))^2) \tag{21}$$
$$\mathbf{w}(j) = \mathbf{w}(j-1) + \Delta\mathbf{w}(j) \tag{22}$$

where $\nabla_{\mathbf{w}}(e_k(j))^2$ is the gradient vector of $(e_k(j))^2$ with respect to the parameter vector $\mathbf{w}$.

f) Repeat step b) to e) for j=j+1.

5. SIMULATION RESULTS

In our simulation experiment, a bandwidth-efficient two-user synchronous CDMA system with system correlation matrix $\mathbf{R} = \begin{pmatrix} 1 & 0.7 \\ 0.7 & 1 \end{pmatrix}$ is considered. The experiment parameters are choosed as: $K = 2, M = 5, \Delta\mathbf{W}(0) = \mathbf{0}, \eta = 10^{-4}, L = 100, \beta = 0.002, \gamma = 0.005$, and $\mathbf{W}$ is initiallized randomly among $\| \mathbf{W} \|^2 < 0.01$. The main results are given in the Table 1 and Table 2. For comparison , the BER performance of conventional detector (Con) and the decorrelator (Dec) is also shown in Table 1 and Table 2.

Table 1: Bit-Error-Rates of Detectors for User 1 ($W_1 = W_2 = 1$)

SNR(1)	Con	Dec	A-MLP
5dB	0.1497	0.102	0.081
10dB	0.1711	0.012	0.0057
15 dB	0.0462	2.9×10^{-5}	1.5×10^{-7}

Table 2: Bit-Error-Rate of Detectors for User 1 ($W_1 = 1, W_2 = 2$)

SNR(1)	Con	Dec	A-MLP
5dB	0.492	0.103	0.083
10dB	0.488	0.012	0.0061
15dB	0.476	2.9×10^{-5}	1.5×10^{-7}

It can be seen from the two tables that the proposed A-MLP detector and the decorrelator have the same ability in overcoming multiple access interferences; However, A-MLP detector has a better bit-error-rate performance than the decorrelator.

6. CONCLUSIONS

In this paper, we have proposed and investigated a new adaptive neural network multiuser detector for synchronous code-division multiple-access (CDMA) systems. The proposed multiuser detector consists of two parts: a decorrelating detector as its auxiliary detector and an adaptive multiple layer perceptron (MLP) detector as its main detector. At the setup stage, the auxiliary detector detect the user's transmitted data and at the same time feeds these output data to the main MLP detector as its learing data, and the main detector learns by using well-known backpropagation (BP) algorithm, and then after the convergence of the learning process, the auxiliary detector stops work and the main detector detects the user's transmitted data and tracks any changes in the system self-adaptively. The proposed detector is a blind one since the pre-known training sequence or knowledges of users' energies are not required, and can provide near minimum bit-error-rate performance since MLP can implement the optimum decision function . The new adaptive neural network multiuser detector performance is verified by computer simulations.

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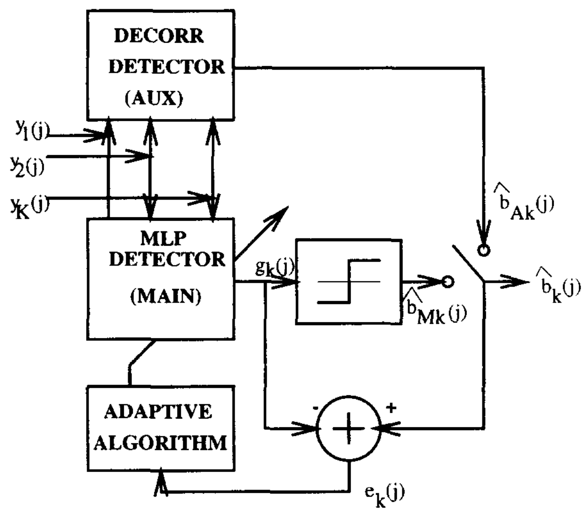

Figure 1: Structure of A-MLP Multiuser Detector