Neural Network-based Receiver for Uplink Multiuser Code Division Multiple Access Communication System

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Abstract. In this paper, the uplink multiuser code division multiple access (CDMA) communication system model is described in the form of space-time domain through antenna array and multipath fading expression. Novel suitable neural network technique is proposed as an effective signal processing method for the receiver of such an uplink multiuser CDMA system. By the appropriate choice of the channel state information for the neural network parameters, the neural network can collectively resolve the effects of both the inter-symbol interference due to the multipath fading channel and the multiple access interference in the receiver of the uplink multiuser CDMA communication system. The dynamics of the proposed neural network receiver for the uplink multiuser CDMA communication system is also studied.

Keywords: neural network, receiver, uplink multiuser CDMA system

1 Introduction

Wireless communications for mobile telephone and data transmission is currently undergoing very rapid development. Many of the emerging wireless systems will incorporate considerable signal processing intelligence in order to provide advanced services such as multimedia transmission [1]. In order to make optimal use of available bandwidth and to provide maximal flexibility, many wireless systems operate as multiple-access systems, in which channel bandwidth is shared by many users on a random access basis. One type of multiple access technique that has become very popular in recent years is code division multiple access (CDMA). CDMA implemented with direct sequence spread spectrum signaling is among the most promising multiplexing technologies for cellular telecommunications services, such as personal communications, mobile telephony, and indoor wireless networks. The advantages of direct-sequence spread-spectrum for these services include superior operation in multipath fading environments, flexibility in the allocation of channels, the ability to operate asynchronously, increased capacity in bursty or fading channels, and the ability to share bandwidth with narrow-band communication systems without undue degradation of either system's performance [2]. CDMA or wideband CDMA is one of the more promising candidates for third-generation (3G) or beyond 3G cellular services [3-4]. Inter-symbol interference (ISI) and multiple access interference (MAI) are two major problems in CDMA or wideband CDMA. Different advanced signal processing techniques have been proposed to deal with these problems. Multiuser detection [5] and space-time processing [6] are the two main category techniques to combat interference and multipath fading channel distortion.

A variety of multiuser detectors have been proposed to deal with MAI through demodulation of mutually interfering signals. However, the computational effort required for the solution of optimum receiver by using conventional multiuser detection and space-time processing methods becomes prohibitively large for real-time implementations [2], [5].

Neural networks [7], [8] are layer networks with output feedback consisting of simple processors (neurons) that can collectively provide good solutions to difficult optimization problems.

With the advent of neural networks, detectors based on well-known structures like multilayer perceptrons [9] were proposed. With increasing attention focused on the application of neural networks to the field of pattern recognition, more neural network–based multiuser detectors were implemented. In [10], [11], Miyajima and Kechriotis uses neural network as the signal processing method for the multiuser receiver under AWGN channel environment and shows to have excellent sub-optimum performance. However, the neural network signal processing method proposed in [10], [11] is unable to exhibit good performance for the uplink multiuser CDMA communication system with both multiple access interference (MAI) and inter-symbol interference (ISI) due to the multipath fading channel. The reason behind this is that neural network parameters set in [10], [11] are not considering the whole channel characteristics of the uplink multiuser CDMA communication system. Recently, blind detectors [12] and kernel-based detectors [13] have been investigated.

In this paper, we consider the signal processing problem by using neural network technique for the receiver of the uplink multiuser CDMA system with both multiple access interference (MAI) and inter-symbol interference (ISI) due to the multipath fading channel. The uplink multiuser CDMA communication system model is described in the form of space-time domain through antenna array and multipath fading expression. By the appropriate choice of the channel state information for the neural network parameters, the neural network can collectively resolve the effects of both the multipath fading and the multiple access interference for the receiver of the uplink multiuser CDMA system.

The rest of the paper is organized as follows. In Section 2, the model of uplink multiuser CDMA communication system is presented. In Section 3, neural network technique is proposed as an effective signal processing method for the receiver of the uplink multiuser CDMA communication system. In Section 4, simulation studies are performed for the evaluation of the system performance of the uplink multiuser CDMA communication systems under different channel situations. In Section 5, conclusions are given.

In what follows, boldface capital (lowercase) letters refer to matrices (vectors), the superscript $(\cdot)^T$ denotes the transpose operation.

2 Communication System Model

The uplink in an asynchronous direct sequence code division multiple access (DS-CDMA) cellular mobile radio network with K active users is considered.

The transmitted baseband signal due to the kth user is given by

$$x_k(t) = A_k \sum_{i=0}^{M-1} b_k[i] s_k(t - iT - q_k),$$
$$k = 1,2,\cdots,K \quad (1)$$

where M, T, $b_k[i]$, respectively denotes, the number of data symbols per frame, the symbol interval, the ith transmitted symbol by the kth user. It is assumed that for each user k, the symbol stream $\{b_k[i]\}$ is a collection of independent equiprobable ± 1 random variables, and the symbol streams of different users are independent. A_k, $s_k(t)$, q_k $(0 \le q_k < T)$, respectively denotes, the amplitude, the normalized signaling waveform, the delay of the kth user's signal.

At the base station receiver, a uniform linear antenna array of P elements is employed. Assume that the channel can be modeled as a tapped delay line with L complex coefficients as the number of resolvable multipaths. The baseband multipath channel between the kth user's transmitter and the base station receiver can be modeled as a single-input multiple-output channel in the form of space-time domain through antenna array and multipath expression.

When the fractionally sampled (oversampled) received signals are used in the digital receivers of the mobile wireless communication systems, oversampling gives rise to cyclostationarity (CS) and provides more statistical information which can be used to improve the communication system performance [2]. Therefore, chip oversampling is used in the base station receiver of the uplink CDMA mobile communication systems. The total received signal vector $\mathbf{y}(t)$, superposed all the users' signals and additive Gaussian noise, is sampled at a multiple $(\overline{m})$ of the chip-rate, i.e., the sampling time interval is $\Delta = (T_c/\overline{m}) = (T/\overline{M})$, where $\overline{M} = \overline{m}N$ is the total number of samples per symbol interval, $\overline{m}$ is the chip oversampling factor.

Denote

$$\mathbf{g}_k(t) = \sum_{j=0}^{N-1} A_k \sum_{l=1}^{L} \mathbf{a}_{kl} g_{kl} \psi(t - jT_c - q_k - \tau_{kl}) \tag{2}$$

$$\mathbf{h}_k(t) = \sum_{j=0}^{N-1} c_k[j] \mathbf{g}_k(t) \tag{3}$$

$$\mathbf{n}(t) = [n_1(t), n_2(t), \cdots, n_P(t)]^T \tag{4}$$

$$v_k = \left\lceil \frac{q_k + \tau_{kl} + T_c}{T} \cdot \frac{T}{T_c} \right\rceil \le \bar{t}_k N \tag{5}$$

$$\bar{t}_k = \lceil (q_k + \tau_{kl} + T_c)/T \rceil \tag{6}$$

$$\bar{t} = \max_{1 \le k \le K} \{\bar{t}_k\} \tag{7}$$

$$m_{smoothing} = \left\lceil (\overline{M} + K)/(\overline{M} - K) \right\rceil \bar{t} \tag{8}$$

where $\mathbf{g}_k(t)$ is the composite channel response vector, taking into account the effects of transmitted power, antenna array response, chip pulse waveform, and the multipath channels. N, $\{c_k[n]\}_{n=0}^{N-1}$, $\psi(t)$, respectively denotes, the processing gain, the binary (± 1) spreading code, the normalized chip waveform of duration T_c. $\mathbf{a}_{kl} = [a_{kl,1}, a_{kl,2}, \cdots, a_{kl,P}]^T$, g_{kl}, τ_{kl}, respectively denotes, the array response vector, the complex gain, the delay, corresponding to the lth path of the kth user's signal. $n_p(t)$ $(1 \le p \le P)$ is the additive Gaussian noise at the pth antenna. $m_{smoothing}$ is the smoothing factor.

Denote following discrete vectors and matrices

$$\mathbf{h}_{k,j} = \left[\mathbf{h}_k[j,0], \mathbf{h}_k[j,1], \cdots, \mathbf{h}_k[j, \overline{M}-1]\right]^T \tag{9}$$

$$\mathbf{g}_{k,j} = \left[\mathbf{g}_k[j,0], \mathbf{g}_k[j,1], \cdots, \mathbf{g}_k[j, \overline{M}-1]\right]^T \tag{10}$$

$$\mathbf{h}_k[j,n] = \sum_{\bar{i}=0}^{N-1} c_{k,j}[\bar{i}]\,\mathbf{g}_k\left(jT + n\Delta - lT_c\right) \tag{11}$$

$$\mathbf{g}_k[j,n] = \mathbf{g}_k\left(jT + n\Delta - lT_c\right) \tag{12}$$

$$\mathbf{h}_{k,j} = \mathbf{C}_{k,j}\mathbf{g}_{k,j} \tag{13}$$

$$\mathbf{C}_{k,j} = \operatorname{diag}\left\{\overline{\mathbf{C}}_{k,j}[0], \overline{\mathbf{C}}_{k,j}[1], \cdots, \overline{\mathbf{C}}_{k,j}[\overline{M}-1]\right\} \tag{14}$$

$$\overline{\mathbf{C}}_{k,j}[n] = \begin{bmatrix} c_{k,j,1}[n] & 0 & \cdots & 0 \\ 0 & c_{k,j,2}[n] & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & c_{k,j,P}[n] \end{bmatrix} \tag{15}$$

$$\mathbf{H}_j = \left[\mathbf{h}_{1,j}, \mathbf{h}_{2,j}, \cdots, \mathbf{h}_{K,j}\right] \tag{16}$$

$$\mathbf{y}_j[i,n] = \sum_{k=1}^{K} \mathbf{h}_k[j,n]\, b_k[i-j] + \sigma \mathbf{n}_j[i,n] \tag{17}$$

$$\mathbf{b}_j[i] = \begin{bmatrix} b_1[i-j] \\ \vdots \\ b_K[i-j] \end{bmatrix} \tag{18}$$

$$\overline{\mathbf{y}}_j[i] = \begin{bmatrix} \mathbf{y}_j[i,0] \\ \vdots \\ \mathbf{y}_j[i, \overline{M}-1] \end{bmatrix} \tag{19}$$

$$\overline{\mathbf{n}}_j[i] = \begin{bmatrix} \mathbf{n}_j[i,0] \\ \vdots \\ \mathbf{n}_j[i, \overline{M}-1] \end{bmatrix} \tag{20}$$

$$\overline{\mathbf{y}}[i] = \begin{bmatrix} \overline{\mathbf{y}}_0[i] \\ \vdots \\ \overline{\mathbf{y}}_{\bar{i}_k}[i] \end{bmatrix} \tag{21}$$

$$\overline{\mathbf{n}}[i] = \begin{bmatrix} \overline{\mathbf{n}}_0[i] \\ \vdots \\ \overline{\mathbf{n}}_{\bar{i}_k}[i] \end{bmatrix} \tag{22}$$

$$\mathbf{b}[i]=\begin{bmatrix}\mathbf{b}_0[i]\\ \vdots\\ \mathbf{b}_{\bar{t}_k}[i]\end{bmatrix} \tag{23}$$

$$\overline{\mathbf{H}}=\begin{bmatrix}\mathbf{H}_0 & \cdots & \mathbf{H}_{\bar{t}_k} & \cdots & \mathbf{0}\\ \vdots & \ddots & \ddots & \ddots & \vdots\\ \mathbf{0} & \cdots & \mathbf{H}_0 & \cdots & \mathbf{H}_{\bar{t}_k}\end{bmatrix} \tag{24}$$

where $j=0,1,\cdots,\bar{t}_k$, $n=0,1,\cdots,\overline{M}-1$, $\mathrm{diag}\{\ \}$ denotes diagonal operation, $\overline{\mathbf{C}}_{k,j}[n]$ is a $P\times P$ matrix, $\overline{\mathbf{H}}$ is a $P\overline{m}N(\bar{t}_k+1)\times K(\bar{t}_k+1)$ matrix. In this paper, we let the chip oversampling factor $\overline{m}=2$, then, we have a $2PN\times 2PN$ matrix $\mathbf{C}_{k,j}=\mathrm{diag}\{\overline{\mathbf{C}}_{k,j}[0],\overline{\mathbf{C}}_{k,j}[1],\cdots,\overline{\mathbf{C}}_{k,j}[2N-1]\}$. For other values of $\overline{m}$, the matrix $\mathbf{C}_{k,j}$ can be similarly constructed. Suppose that user k is the user of interest, and at every based station received antenna p, $(p=1,2,\cdots,P)$, for every propagation path j, ($j=0,1,\cdots,\bar{t}_k$), the spreading sequence $\{c_{k,j,p}[0],c_{k,j,p}[1],\cdots,c_{k,j,p}[2N-1]\}$ is known to the receiver (and therefore $\mathbf{C}_{k,j}$ is known to the receiver). Then, the received discrete signals can be expressed in a matrix form as

$$\overline{\mathbf{y}}[i]=\overline{\mathbf{H}}\,\mathbf{b}[i]+\sigma\overline{\mathbf{n}}[i] \tag{25}$$

where $\overline{\mathbf{y}}[i]$, $\overline{\mathbf{n}}[i]$, $\mathbf{b}[i]$, $\overline{\mathbf{H}}$ are, respectively, a $P\overline{m}N(\bar{t}_k+1)\times 1$ received signal vector, a $P\overline{m}N(\bar{t}_k+1)\times 1$ independent zero-mean complex white Gaussian noise vector with variance of σ^2, a $K(\bar{t}_k+1)\times 1$ transmitted symbol vector, a $P\overline{m}N(\bar{t}_k+1)\times K(\bar{t}_k+1)$ multipath channel matrix.

3 Neural Network-based Receiver

From equation (25), based on the minimization of the likelihood function, the transmitted symbol vector of the optimal receiver can be estimated as [5]

$$\hat{\mathbf{b}}[i]=\arg\min\left\{\left\|\overline{\mathbf{y}}[i]-\overline{\mathbf{H}}\,\mathbf{b}[i]\right\|^2\right\}=\arg\min\left\{-\overline{\mathbf{y}}[i]^T\overline{\mathbf{H}}\mathbf{b}[i]+\frac{1}{2}\mathbf{b}[i]^T\overline{\mathbf{H}}^T\overline{\mathbf{H}}\,\mathbf{b}[i]\right\} \tag{26}$$

Note that if the value of $P\overline{m}N(\bar{t}_k+1)$ is relatively large, even for a small-to-moderate number of users K, the computational effort required for the solution of (26) becomes prohibitively large for real-time implementations.

Neural networks are layer networks with output feedback consisting of simple processors (neurons) that can collectively provide good solutions to difficult optimization problems. Neural networks have been employed extensively to solve a variety of difficult combinatorial optimization problems [7]-[19].

Next, we will transform the minimization of the likelihood function given in (26) into the minimization of neural network energy function E_{NN} described by the expression

$$E_{\mathrm{NN}}=-\mathbf{OI}-\frac{1}{2}\mathbf{OMO} \tag{27}$$

By setting $\mathbf{I}=\overline{\mathbf{y}}[i]\overline{\mathbf{H}}^T$ and $\mathbf{M}=-\overline{\mathbf{H}}^T\overline{\mathbf{H}}$, then in (27), $\mathbf{O}$ is the output of neural network neurons and $\mathbf{M}$ is the interconnection matrix between neural network neurons.

Once the above transformation is done, the sub-optimum estimation of the transmitted symbol vector could be simply driven from the neural network receiver output by using

$$\hat{\mathbf{b}}[i]\approx\mathbf{O} \tag{28}$$

From equation (25) to equation (28), we can see that by the appropriate choice of the channel state information used for the neural network parameters, the neural network can collectively resolve the effects of both the inter-symbol interference due to the multipath fading and the multiple access interference in the receiver of the uplink multiuser CDMA communication system.

The channel state information is very crucial to the proposed neural network receiver of the uplink multiuser CDMA communication system. Imperfections in channel state information degrade the neural network receiver performance. Channel estimation can be achieved by sending training sequences, using pilot channel, or using blind methods. Periodic transmission of training sequences make the identification of channel state information feasible since both input and output signals are known during the transmission of these sequences.

In the following, more information about the dynamics of neural network receiver will be discussed.

The dynamic equation implemented by the neural network energy function E_{NN} is

$$C_i\frac{do_i}{dt}=-\frac{\partial E_{\mathrm{NN}}}{\partial o_i}(\mathbf{O})-G_io_i \quad , \quad i=1,\cdots,P\overline{m}N(\bar{t}_k+1) \tag{29}$$

Where C_i is the output capacity and G_i is the parasite conductance of neuron i. Assuming for simplicity that $C_i=C$ and $G_i=G$ for all the neurons, then, the dynamic behavior of the neural network energy function E_{NN} is

$$\frac{dE_{NN}}{dt}=-\sum_{i=1}^{P\overline{m}N(\bar{t}_k+1)}C\left(\frac{do_i}{dt}\right)^2 \tag{30}$$

Equation (30) shows that the neural network energy function E_{NN} goes toward the minimum value. Thus, for any initial value, the neural network evolves toward the minimum, and the energy function has a global minimum point.

The gradient of the neural network energy function E_{NN} is

$$\nabla E_{NN}(\mathbf{O})=-\mathbf{I}-\mathbf{MO} \tag{31}$$

Equation (31) shows that the neural network energy function E_{NN} has a unique minimum value $\hat{\mathbf{O}}_{\mathrm{opt}}=-\mathbf{M}^{-1}\mathbf{I}$. It is important to note that the minimum value derived according to the above procedure equals to the optimum minimum value

$$\mathbf{O}_{\mathrm{opt}}=-\mathbf{M}^{-1}\mathbf{I} \tag{32}$$

From above discussion, we can see that the neural network energy function has a global minimum point and is stable for any initial value.

Therefore, the implementation of the neural network based receiver proposed for the uplink multiuser CDMA communication system is feasible.

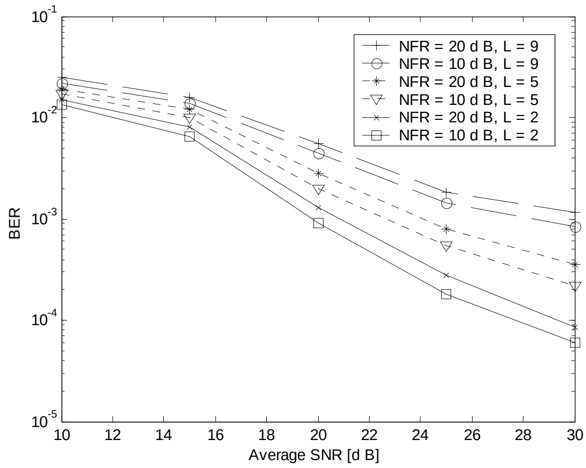

Figure 1. System performance of matched-filter-based neural network method proposed in [10], [11] under different channel situations.

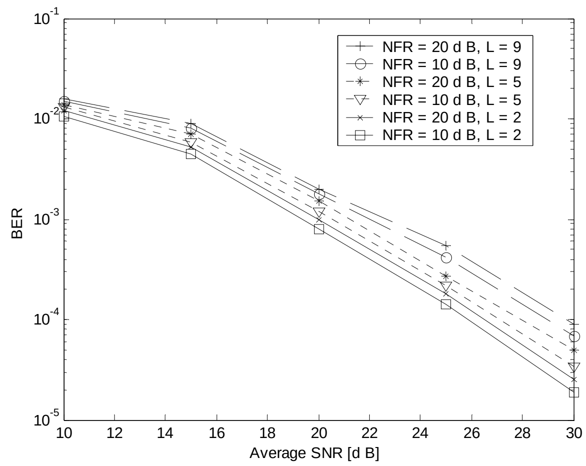

Figure 2. System performance of channel-state-information-parameters-assisted neural network method proposed in this paper under different channel situations.

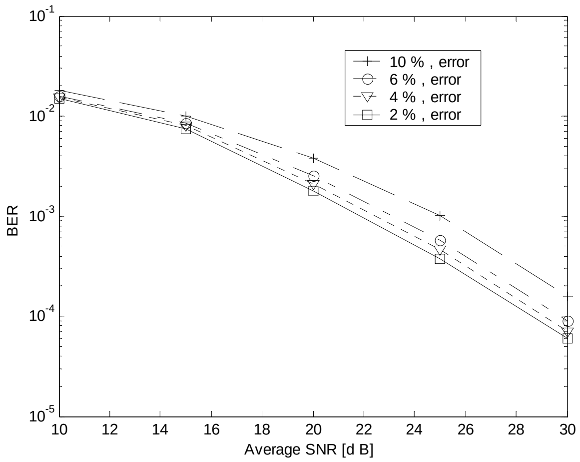

Figure 3. System performance of channel-state-information-parameters-assisted neural network method proposed in this paper with different errors of the channel state information parameters.

4 Performance Evaluation

The simulated CDMA system is an asynchronous system adopting $N = 31$ Gold codes as spreading sequences, with users $K = 15$, antenna elements $P = 3$, multipath diversity order $L = 2$, $L = 5$ or $L = 9$, the number of symbols per frame is $M = 300$, the chip pulse is a raised cosine pulse with roll-off factor 0.5, the initial delay q_k of each user is uniformly generated on $[0, LT_c]$, the delay of each path τ_{kl} is uniformly generated on $[0, LT_c]$. The modulation scheme is BPSK.

In the following, the system performance studies of the method proposed in [10], [11] (we call it the matched-filter-based neural network method) are provided for the references with the proposed method in this paper (we call it the channel-state-information-parameters-assisted neural network method).

When the matched-filter-based neural network method proposed in [10], [11] is used as the signal processing method, the simulated bit error rate (BER) versus average signal-to-noise ratio (SNR) performance is shown in figure 1 for different near-far ratio (NFR) and different multipath diversity order L.

From figure 1, we can see that the BER versus average SNR performance of the matched-filter-based neural network method proposed in [10], [11] is unable to resistant to the inter-symbol interference (ISI) due to the multipath fading channel (with different multipath diversity order L). When the average SNR is larger than 20 dB, the BER versus average SNR performance of the matched-filter-based neural network method proposed in [10], [11] becomes much worse as the multipath diversity order is increasing.

When the channel-state-information-parameters-assisted neural network method proposed in this paper is used as the signal processing method, the simulated bit error rate (BER) versus average signal-to-noise ratio (SNR) performance is shown in figure 2 for different near-far ratio (NFR) and different multipath diversity order L. (The channel estimation method proposed in [20] is used here to estimate the channel state information for the neural network parameters.)

From figure 2, we can see that the channel-state-information-parameters-assisted neural network method proposed in this paper can collectively resolve the effects of both the multipath fading (with different multipath diversity order L) and the multiple access interference (with different near-far ratio NFR). When the average SNR is larger than 20 dB, the BER versus average SNR performance of the channel-state-information-parameters-assisted neural network method proposed in this paper becomes only a little worse as the multipath diversity order is increasing and the near-far ratio is increasing.

Since the accuracy of the channel state information for the neural network parameters is very crucial to the channel-state-information-parameters-assisted neural network method proposed in this paper, the system performance affected by the error in the channel state information parameters will be studied in the following.

When near-far ratio (NFR) is $\mathrm{NFR} = 10\ \mathrm{dB}$ and multipath diversity order is $L = 5$, the average simulated bit error rate (BER) versus signal-to-noise ratio (SNR) system performance for the case in which the channel state information parameters delivered to the proposed channel-state-information-parameters-assisted neural network receiver contains different errors are shown in figure 3.

From figure 3, we can see that the less the error in the channel state information parameters, the better the channel-state-information-parameters-assisted neural network receiver performance.

5 Conclusions

In this paper, a novel suitable neural network technique is proposed as an effective signal processing method for the receiver of the uplink multiuser CDMA system. The dynamics of the proposed neural network receiver for the uplink multiuser CDMA communication system is discussed. Simulation studies show that the proposed neural network receiver can collectively resolve the effects of both the inter-symbol interference due to the multipath fading channel and the multiple access interference in the receiver of the uplink multiuser CDMA communication system if the channel state information for the neural network parameters is appropriately chosen. The accuracy of the channel state information for the neural network parameters is crucial to the system performance of the proposed neural network receiver for the uplink multiuser CDMA communication system.

Acknowledgments

This work was supported in part by the National Science Foundation of China (No. 60602021, No.

60772119), the Specialized Research Fund for the Doctoral Program of Higher Education (No. 20060151001), the Excellence Young Talent Fund of Dalian (No. 2006J23JH037), the open research fund of Nation Mobile Communications Research Laboratory of Southeast University (No. A200606).

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