Blind Adaptive Multiuser Detection Using a Recurrent Neural Network

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Abstract-- **Multiuser detection has gained much attention in recent years for its potential to greatly improve the capacities of CDMA communication systems. In this paper, a recurrent neural network is presented for solving the nonlinear optimization problem involved in the multiuser detection in CDMA. Compared with other neural networks, the presented neural network can globally converge to the exact optimal solution of the nonlinear optimization problem with nonlinear constraints and has relatively low structural complexity. Computer simulation results are presented to show the optimization capability. The performance in CDMA communcation systems is also studied by means of simulation**

Keywords: CDMA, Multiuser Detection, blind adaptive detection, recurrent neural networks, nonlinear optimization

I. INTRODUCTION

In wireless communication systems, Direct-Sequence Code Division Multiple Access (DS-CDMA) is a promising technology, with several advantages over others: asynchronous multiple access, robustness to frequency selective fading, and etc [1]. But to permit a high number of user communicating simultanously with high bit rate in 3G mobile communication systems, the capacity has to be increased. The capacity of DS-CDMA is limited by signal interference. Therefore it can be increased by using techniques that suppress interference. Many research activities have been focused on the MultiUser Detection (MUD) techniques [1][2]. Among them, blind detection is the most promising one because it requires no more knowledge than does the conventional single-user detection: the desired user's signature waveform and its timing. The blind detection techniques turns the MUD problem to a constrained nonlinear optimization of the objective function Minimum Output Energy (MOE). Based on this, Verdú proposed the adaptive blind detection which gives an adaptive solution to the nonlinear optimization to reduce the computation complexity [3]. As the cost, adaptive blind detection needs for a certain number of bit intervals to reach the optimal solution, since the path towards the optimum filter coefficients set is performed in a step by step approximation, based on the steepest descent gradient technique.

Wireless communication channels are time-varying rapidly, because of both natural communicating conditions (like multipath fading, mobile terminal moving, etc.) and random asynchronous access of other interfering users. So the wireless communication systems are typical real-time systems. This requires that the detection methods should adapt the parameters rapidly to achieve good performance.

Neural network approaches have shown to be able to handle real-time applications, because of VLSI implementability and parallel processing capability [4]. The idea proposed in this paper is to employ a recurrent neural network in order to accelerate the convergence process of the adaptive filter coefficients towards the optimum solution in the blind detection algorithm.

After Hopfield and Tank's seminal work, Kennedy and Chua developed a neural network with a finite penalty parameter for solving nonlinear programming problems [4]. Although this work actually fullfills both the Kuhn-Tucker optimality conditions in terms of penalty function, this network is not capable to find an exact optimal solution due to a finite penalty parameter and is difficult to implement when the penalty parameter is very large. Fantacci, Forti, and et al, developed a blind detector/receiver based on Kennedy and Chua's neural network [5]. Kechriotis and Manolakos [11] investigated the application of Hopfield neural networks (HNN's) to the problem of multiuser detection in spread spectrum/CDMA (code division multiple access) communication systems. Recently, Xia and Wang proposed a recurrent neural network that can solve nonlinear convex optimization problems [6][7]. Xia and Wang's neural network is stable in the sense of Lyapunov and globally convergent to the exact optimal solution. Applying Xia and Wang's neural network, we proposed a neural network approach to blind multiuser detection. The simulation results show that it is efficient in blind detection of CDMA.

The rest of this paper is organized as follows. In Section II., we briefly review the DS-CDMA communication system and derive the formulation for blind detection. In Section III., we present the neural network architecture. Simu-

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lation results are reported in Section IV.. Finally, Section V. concludes this paper.

II. Problem Formulation

Multiaccess communication, in which several transmitters share a common channel, is common nowadays, like mobile communication systems, satellite communication systems, packet-radio networks, and etc. A common feature of those communication channels is that the receiver obtains a noisy version of the superposition of the signal sent by active transmitters. How to detect the desired signal is important for these communication systems.

The conventional DS-CDMA system treats each user as signal, with other users considered as noise or MAI (Mulitple Access Interference). This technique has several inherent shortcomings. Simply considering other users as noise makes the capacity interference-limited. For the same reason the near/far effect is very serious, so the system needs good power control [1].

To solve these problems, the MultiUser Detection (MUD) method was proposed by Verdú. MUD considers all users as signals when detecting a particular user signal; so this is a joint detection (in comparison to the sperate detection discussed previous). This technique can reduce interference and hence lead to increase capacity. At the same time it alleviates the near/far problem.

The optimum multiuser detector for asynchronous mulitple-access Gaussian channels is discussed in [1] where it is shown that the near/far problem suffered by the conventional CDMA receiver can be overcome by a more sophisticated receiver which accounts for the presence of other interferers in the channel. This receiver is shown to attain essentially single-user performance upon knowing the following [2]:

① The signature waveform of the desired user.

② The signature waveform of the interfering users.

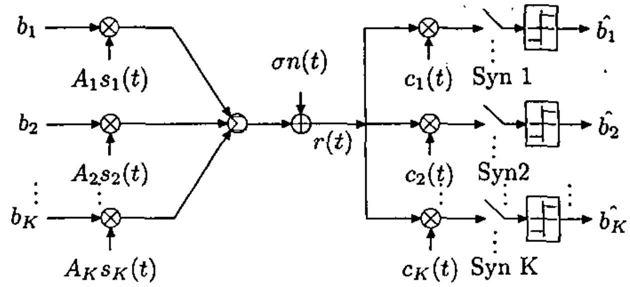
③ The timing of the desired user.

④ The timing of each interfering user.

⑤ The received relative amplitudes of the interfering users to that of the desired user.

The conventional receiver only requires ① and ③, but it is severely limited by the near/far problem, even in the presence of perfect power control, the bit-error-rate is orders of magnitude far from optimal.

To alleviate the need to know interferers' signature ②, timing ④, and amplitudes ⑤, some attention has been focused recently on adaptive multiuser detection. The adaptive multiuser detector in [3] is based on the minimization of mean-square-error (MMSE) between the outputs and the data. But it needs traing data sequences for each user to approximate the unknown parameters. However, at any time there may be a drastic change in the communication environment (e.g. a deep fade or the access of other interfering users), at this time the parameters becomes unreliable. Then data transmission of the desire user must be temporarily suspened and a fresh training sequence must be retransmitted. Thus retransmitting of the training sequence is cumbersome in most CDMA systems, where one of the most important advantages is the ability to have completely asynchronous and uncoordinated transmissions that switch on and off autonomously.



$$r(t) = \sum_{k=1}^{K} A_k b_k s_k(t) + \sigma n(t) \quad t \in [0, Tb]$$
$$\hat{b_k} = sgn[\langle c_k(t), r(t)\rangle] = sgn[\int_0^{T_b} r(t) c_k(t)]$$
$k = 1, \ldots, K, \quad T_b$ is the bit interval

Figure 1: Simplified K-user DS-CDMA Synchronous Communication Model

The foregoing observation implies that the need for blind adaptive receivers is even more evident in multiaccess channels than in single-user channels subject to intersymbol interference.

The formulation of blind adaptive multiuser detection is discussed as follows.

Let's consider the DS-CDMA systems as illustrated in Figure 1, where $b_k \in \{-1, 1\}$ is the bits to be transmitted, $s_k(t)$ is the kth user's signature waveform, A_k is the modulation amplitude, $\sigma n(t)$ is the additive Gaussian white noise, $r(t)$ is the received signal, and $c_k(t)$ is the matched filter coefficients. The commonly used objective function to be minimized in multiuser detection is:

$$\text{MMSE}(c_k(t)) = \min_{c_k} E[(b_k - \langle c_k(t), r(t)\rangle)^2]$$

where $\langle c_k(t), r(t)\rangle = \int_0^{T_b} c_k(t) r(t) dt$, $c_k(t)$ is the waveform used to demodulate $r(t)$. The output decision is

$$\hat{b_k} = sgn[\langle c_k(t), r(t)\rangle]$$

It can be proven that the solution of this optimization problem has no relation with b_k.

For simplicity, we will concentrate on the first user only from now. The canonical representation of linear MMSE is

$$c_1(t) = s_1(t) + x_1(t), \text{ and } \langle s_1(t), x_1(t)\rangle = 0$$

Define Mean Output Energy of user 1 as

$$MOE(x_1(t)) = E[(\langle r(t), s_1(t) + x_1(t)\rangle)^2]$$

Then

$$\begin{aligned} &\mathrm{MSE}(x_1(t)) = \mathrm{E}[(A_1 b_1 - \langle r(t), s_1(t) + x_1(t)\rangle)^2] \\ &= A_1^2 + \mathrm{MOE}(x_1(t)) - 2A_1\langle s_1(t), s_1(t) + x_1(t)\rangle \\ &= \mathrm{MOE}(x_1(t)) - A_1^2 \end{aligned}$$

So the solution of MMOE is also the solution of MMSE. While MMOE has no nothing to do with b_k, then the detection problem evolves to the following form:

$$\begin{array}{ll} \min & \mathrm{MOE}(x_1(t)) = \mathrm{E}[(\langle r(t), s_1(t) + x_1(t)\rangle)^2] \\ \text{s.t.} & \langle s_1(t), x_1(t)\rangle = 0 \end{array}$$

Because the received signature $\hat{s}_1$ is not always the same as s_1, so we need to add the surplus energy constraints [3]:

$$||x_1(t)||^2 < \chi$$

where χ is the surplus energy which is a positive constant. So the formulation for Blind MMOE Detector with surplus energy constraints can be expressed as follows,

$$\begin{array}{ll} \min & \mathrm{MOE}(x_1(t)) = E[(\langle r(t), s_1(t) + x_1(t)\rangle)^2] \\ \text{s.t.} & \langle s_1(t), x_1(t)\rangle = 0\,, \\ & ||x_1(t)||^2 \leq \chi \end{array} \qquad (1)$$

It is proven that $\mathrm{MOE}(x_1)$ is a convex function [1].

The nonlinear optimization problem (1) is a general form. Particularly, when the signature waveforms $s_k(t), (k = 1, \ldots, K)$ are binary PN sequences, the vector form of (1) is as follows.

$$\begin{array}{ll} \min & \mathrm{MOE}(x_1) = E[(\langle r, s_1 + x_1\rangle)^2] \\ \text{s.t.} & \langle s_1, x_1\rangle = 0\,, \\ & ||x_1||^2 \leq \chi \end{array} \qquad (2)$$

where $x_1, s_1, y_1 \in R^n$, n is the number of chips per bit for the PN sequences. From now on, we will design the neural network based on formulation (2).

III. Neural Network Architecture

Problem (2) can be generalized to the following formulation:

$$\begin{array}{ll} \min & f(u) \\ \text{s.t.} & g(u) \leq 0 \\ & h(u) = 0 \end{array} \qquad (3)$$

where, $u \in R^n$, $f(u), g(u), h(u)$ are scalar functions.

In [7], Xia and Wang developed a neural network for solving the following nonlinear optimization problem with inequality constraints.

$$\begin{array}{ll} \min & f(u) \\ \text{s.t.} & c(u) \leq 0, \quad u \geq 0 \end{array}$$

In addition in [6], Xia and Wang developed a neural network for solving the following nonlinear optimization problem with both equality and inequality constraints.

$$\begin{array}{ll} \min & \frac{1}{2}u^T Q u + q^T u \\ \text{s.t.} & g(u) \leq 0, \quad G^T u = -f_{ext} \end{array}$$

Following these design methods, here we present a recurrent neural network for solving the nonlinear program (3). For complete proof, please refer to [6][7].

To derive a neural network model for solving (3), we first give a equivalent form of (3).

$$\left\{ \begin{array}{rcl} \nabla f(u) + v\nabla g(u) - wh(u) & = & 0, \\ (v + g(u))^+ - v & = & 0, \\ h(u) & = & 0, \end{array} \right. \qquad (4)$$

where $v \in R$, $w \in R$ are both auxiliary one-dimensional variables.

It can be derived as follows. First define the Lagrangian function

$$L(u, v, w) = f(u) + vg(u) - wh(u)$$

According to the well-known saddle point theorem [8], u^* is a solution to (3) if and only if there exists $v^* \in R^+$ and $w^* \in R$, such that for any $(u, v, w) \in R^n \times R^+ \times R$, (u^*, v^*, w^*) satisfies

$$L(u^*, v, w) \leq L(u^*, v^*, w^*) \leq L(u, v^*, w^*)$$

where $R^+ = \{v \in R \mid v \geq 0\}$. Then we can get

$$L(u^*, v, 0) \leq L(u^*, v^*, w^*) \leq L(u, v^*, w^*)$$

Because $h(u^*) = 0$, so

$$\begin{array}{rl} & f(u^*) + vg(u^*) \\ \leq & f(u^*) + v^*g(u^*) \\ \leq & f(u) + v^*g(u) - w^*h(u) \end{array}$$

From the first inequality above, we can derive that

$$(v - v^*)(-g(u^*)) \geq 0, \ \ \forall v \geq 0$$

On the other side, let

$$\phi(u) = f(u) + v^*g(u) - wh(u)$$

Then the right inequality above implies:

$$\phi(u) \geq \phi(u^*), \ \ \forall u \in R^n$$

this means,

$$\nabla\phi(u^*) = 0$$

that is,

$$\nabla f(u^*) + v^*\nabla g(u^*) - w^*\nabla h(u^*) = 0$$

so, u^* is a solution to (3), if and only if (u^*, v^*, w^*) satisfies

$$\left\{ \begin{array}{rcl} \nabla f(u^*) + v^*\nabla g(u^*) - w^*\nabla h(u^*) & = & 0 \\ (v - v^*)(-g(u^*)) & \geq & 0, \ \forall v \geq 0 \\ h(u^*) & = & 0 \end{array} \right. \tag{5}$$

From the projection theorem [9], it can be seen that the above formulation is equivalent to (4).

Based on the equivalent formulation in (4), we propose a recurrent neural network for solving (3) with its dynamical equation given by

$$\frac{d}{dt}\begin{pmatrix} u \\ v \\ w \end{pmatrix} = \lambda \begin{pmatrix} -\nabla f(u) - v\nabla g(u) + w\nabla h(u) \\ (v + g(u))^+ - v \\ -h(u) \end{pmatrix} \tag{6}$$

where λ is a positive scaling constant.

The neural network is guaranteed to be globally convergent to the exact optimal solution [6][7].

Now for the problem (2), the specific neural network can be defined by the following dynamic state equation.

$$\frac{d}{dt}\begin{pmatrix} x_1 \\ v \\ w \end{pmatrix} = \lambda \begin{pmatrix} -2\mathrm{E}[r^T(x_1 + s_1)r] - 2vx_1 - ws_1 \\ (v + ||x_1||^2 - \chi)^+ - v \\ -s_1^T x_1 \end{pmatrix} \tag{7}$$

where $x_1, s_1, r \in R^n$, n is the number of chips per bit. $v \in R$, $w \in R$, $\lambda > 0$ is a scalar parameter.

In [5], R. Fantacci, et al. also investigated the neural network approach to solve the problem (2). They proposed a recurrent neural network with nonobvious modification of Kennedy and Chua's neural network [4]. It can be defined by the following equation.

$$\dot{x_1} = -Gx_1 - \nabla V(x_1) + \langle \nabla V(x_1), s_1 \rangle s_1 \tag{8}$$

where

$$\begin{array}{l} V(x_1) = \mathrm{MOE}(x_1) + \int_0^{f(x_1)} g(\rho)d\rho\,, \\ f(x_1) = \chi - ||x_1||^2\,, \\ g(\rho) = \left\{ \begin{array}{ll} 0, & \text{for } \rho \leq 0 \\ K\rho, & \text{for } \rho < 0 \end{array} \right. \end{array}$$

$x_1 \in R^n$, $G \in R^+$ models the neuron parasitic capacitances, and K is the positive penalty parameter.

IV. Simulation Results

To verify the neural network (8), Fantacci, et al. used the following example problem.

$$\begin{array}{ll} \min & \mathrm{MOE}(u) = \frac{1}{2}u^T Q u + q^T u \\ \text{s.t.} & s^T u = 0\,, \\ & ||u||^2 \leq \chi \end{array}$$

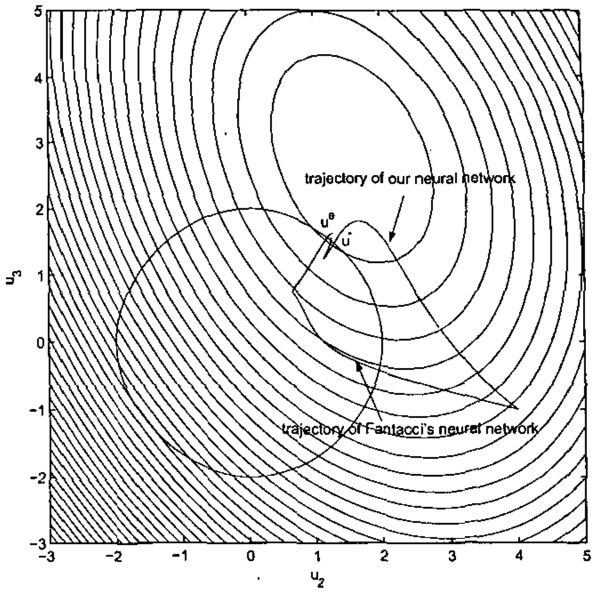


Figure 2: Trajectories of two Neural Networks

where,

$$Q = \begin{pmatrix} 10 & 2 & 1 \\ 2 & 12 & 3 \\ 1 & 3 & 7 \end{pmatrix}, \ q = \begin{pmatrix} 23 \\ -27 \\ -24 \end{pmatrix},$$

$$s = (1 \ 0 \ 0)^T, \ \chi = 4, \ u \in R^3$$

We will also use this problem to demonstrate the optimization capability of the neural network (7).

Figure 2 depicts the contour lines of the objective function, and the constraint circle $||u||^2 = u_2^2 + u_3^2 = \chi = 4$. In this figure, two simulated trajectories are plotted, separately of Fantacci's neural network (8) and of the neural network (7) both starting from point $(2, 4, -1)$. It can be seen that the trajectory of Fantacci's neural network (8) converges toward the equilibrium point u^e, which is close to the minimum u^*, while the trajectory of neural network (7) converges exactly toward the optimal point u^*. For Fantacci's neural network (8), the accuracy of solution, i.e., the closeness of u^e and u^* depends on the value of the penalty parameter K.

In Figure 3, the convergence of u_1 with time is illustrated. From this figure, it can be easily seen that the neural network (7) converges with more accuracy than the Fantacci's neural network (8) within the same period of time and under the same corresponding parameters.

The performance of the neural network (7) in a DS-CDMA mobile communication systems is also studied by means of computer simulation. It shows that the neural network is efficient in blind adaptive multiuser detection. Compared with the classic blind adaptive detector [3], the neural network permits to gain better performance in terms of bit error rate (BER).

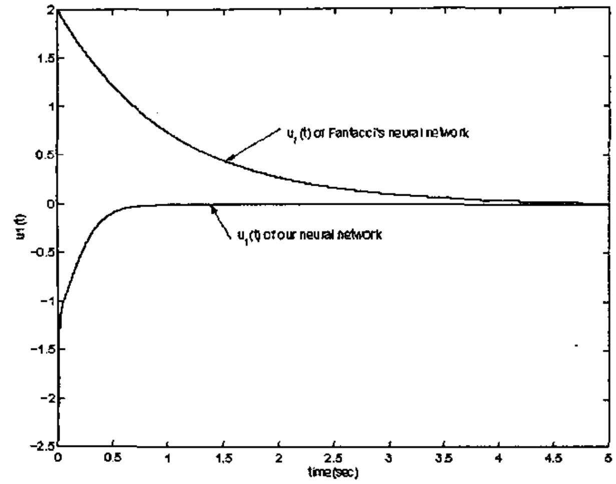


Figure 3: Convergence of $u_1(t)$ of two Neural Networks

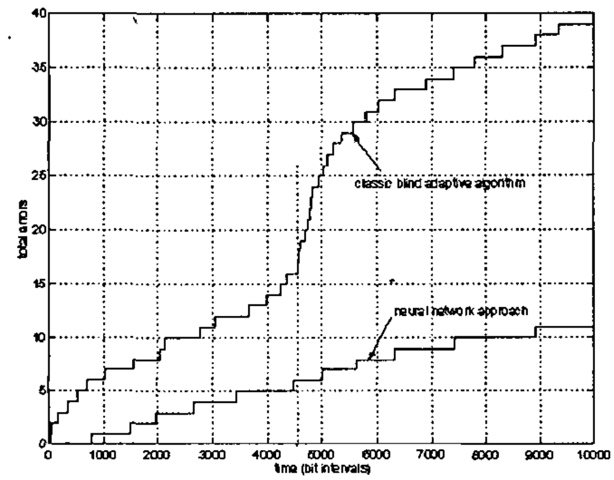


Figure 4: Total number of errors versus number of bits

The simulated system uses 31 chips per bit Gold PN sequences [1] as the signature codes. We assume that it is under perfect power control; i.e., $A_1 = A_2 = \ldots = A_K$. The communcation channel is an additive Gaussian white noise (AGWN) channel and the signal noise ratio (SNR) is 20dB. For brevity, we only detect the first user's signal.

Figure 4 depicts the case when only one user is transmitting in the first 4500 bit time periods, and suddenly 19 other interfering users begin to transmit. In this circumstance, the communication channel for the first user at 4500 bit interval is under a rapid change. As shown in Figure 4, the neural network (7) can rapidly adapt its parameters to the optimum, while the classic blind adaptive detector needs a few steps for its parameters to reach the steady state and therefore in the adaptation period the error bit rate (EBR) is much higher.

V. CONCLUSIONS

In this paper, we present a recurrent neural network to solve the nonlinear optimization problem for multiuser detection in CDMA communication systems. The recurrent neural network is globally convergent to the exact optimal solution. Simulation results have shown that the recurrent neural network is effective for the blind detection, and leads to the capacity increase for the CDMA systems.

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