A Neural Network Based CDMA Detector with Robust Near-Far Resistance

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Abstract

In code division multiple access (CDMA), high efficiency for spectrum usage and robust jamming resistance have been increasingly important. However, the inherent near-far problem is an impediment. Although deliberate power control algorithm can partially solve this problem, the cost is high. In this paper, a compact neural network based detector for CDMA is proposed. By proper array processing and applying hardware annealing technique, the VLSI implementation of optimal multiuser detector (OMD) is suitable.

1 Introduction

With advanced development of wireless communication and strong demand for high capacity and high quality communication systems, novel communication techniques in mobile systems, CT-2, satellites, wireless asynchronous transfer modes (ATM), mobile personal computers, etc, are widely used. Among these techniques code division multiple access (CDMA) have received significant attention due to its high spectral efficiency and robust resistance of multipath and jamming effects [1]. Generally, 11 subscribers can be accomodated per Megahertz per base-station for Advanced Mobile Phone Service (AMPS); 85 for Global Mobile System (GSM); and 283 for CDMA. Besides, the CDMA standards TIA/EIA IS-95A (cellular) and ANSI J-STD-008 (PCS) have been built for commercial use. Part of the uplink block diagram for IS-95 is shown in Figure 1 [2]. CDMA is a technique of spread spectrum communication. Each user is assigned a distinct pseudonoise (PN) code. If every user's code is uncorrelated with any other users', all the traffic channels within one cell can share the same bandwidth simultaneously.

To maintain high quality and high spectral efficiency in CDMA systems, controlling signal power of users is very Important. In satellite communication, the high-power and low-power transmitters co-exist. In ground communication, some users may be near the base-station and some may be far away. 60 dB more or more signal power difference at the base-station for two mobiles is quite possible. When an unwanted user's received signal is much larger than the received signal power contributed by the desired user, the perfromance of CDMA is seriously impaired in the radio environment. This is called near-far problem and is a major technical obstacle in CDMA. In 1986, S. Verdu [3] showed that the optimal near-far resistant detector could be achieved by minimizing an integer quadratic object function. It means multiuser detection in CDMA can be converted into an optimization problem.

Compact neural networks have shown great promise in solving many complex signal detection and optimization problems that can not be addressed satisfactorily with conventional approaches [4]. This motivates the research efforts by using compact neural networks to implement the optimal multiuser detectors (OMDs). Baaoed upon the feasibility of VLSI implementation, an algorithm of compact neural network as a parallel computational framework of OMD for CDMA is proposed. By mappmg the quadratic object function of OMD onto the Lyapunov function associated with compact neural network, the desired estimate can be obtained. Optimum solutions can be facilitated by applying the paralleled hardware annealing [5]. The annealed compact neural network multiuser detector does not required good initial states and can provide results similar to that from the OMD.

2 Conventional Detector and Optimized Decision Rule of CDMA Detector

For illustration purpose, K active users for the same synchronous Gaussian channel in a direct-sequence CDMA (DS-CDMA) system at a given time t is considered. All the carrier phases are assumed to be zero. There are K different signature waveforms $\{s_k(t), k = 1,2,\ldots, K\}$. Each waveform s_k is composed of a string of bits $\{b_k(i) \in \{-1, +1\}\}$. In a DS-CDMA system, the received signal is

$$r(t) = \sum_{k=1}^{K} b_k(i) s_k(t - iT) + n(t) \qquad t \in [iT, (i+1)T]. \quad (1)$$

where $n(t)$ is Gaussian noise. If focus is centered on one symbol interval in (1), the function of a detector is to recognize every active user's symbol at the specified interval. Performance of conventional detector and optimal multiuser detector (OMD) is discussed.

2.1 Conventional Detector

A conventional detector consists of K filters matched to the signature waveforms of K subscribers. Each signature waveform (or PN code) s_k is reconstructed and correlated with the received signal r(t). After passing through the matched filter bank, r(t) becomes K parallel outputs. The K outputs are sampled at the bit time. Simple decision devices following the matched filters provide every user's symbol estimates based upon the signs of the output of the matched filters.

$$\begin{aligned} y_k^{(i)} &= \int_{iT}^{(i+1)T} r(t)s_k(t - iT)dt, \\ \mathbf{b}_{\mathbf{CD}}^{(\mathbf{i})} &= sign(\mathbf{y}^{(i)}) \end{aligned} \qquad (2)$$

where $\mathbf{b}_{CD}^{(i)} = [b_1^{(i)} b_2^{(i)} \cdots b_K^{(i)}]^T$ and $\mathbf{y}^{(i)} = [y_1^{(i)} y_2^{(i)} \cdots y_K^{(i)}]^T$. The block diagram is shown in Figure 2. Multiple access interference (MAI) has significant effect on the performance and capacity of conventional detectors. In addition, the near-far problem is not solved in conventional detector. To achieve better performance, optimal multiuser detector was developed. not only improves the performance but also reduces the precision requirements for power control. Besidea, reducing interference in uplink also means the same transmitted power can be used for a larger coverage of a cell. Power utilization also becomes more efficient.

2.2 Optimal Multiuser Detector

By minimizing the noise energy, an OMD can be derived. The minimization is equivalent to maximize the logarithm of the likelihood function. The matrix representation of y is

$$\mathbf{y} = \mathbf{H}\mathbf{b} + \mathbf{n}, \qquad (3)$$

where $\mathbf{n} = [n_1^{(i)} n_2^{(i)} \cdots n_K^{(i)}]^T$ Here $\mathbf{H} \in R^{K\times K}$ is a cross correlation matrix of the signature waveforms,

$$h_{ij} = \int_0^T s_i(t) \cdot s_j(t)dt. \qquad (4)$$

The matrix H is nonnegative definite. Given the observation $r(t)$, the OMD is to generate an estimate $\hat{\mathbf{b}} = [\hat{b}_1, \hat{b}_2, \cdots, \hat{b}_K]^T$ to minimize the cost function [3],

$$\hat{\mathbf{b}}_{OMD}^{(i)} = arg \min_{b\in\{-1,+1\}^K} \int_0^T \left[r(t) - \sum_{k=1}^{K} b_k s_k(t) \right]^2 dt. \qquad (5)$$

Notice that (5) can be written in a matrix form,

$$\hat{\mathbf{b}}_{OMD}^{(i)} = \min_{b\in\{-1,+1\}^K} \frac{1}{2}\mathbf{b}^T\mathbf{H}\mathbf{b} - \mathbf{b}^T\mathbf{y}. \qquad (6)$$

In (6), the optimized multiuser detection problem becomes a quadratic optimization problem. Considering the intented hardware implementation of an OMD, compact neural network can be chosen due to its shift-invariant and collective computational properties. The energy function of a compact neural network [6] which is stable for processing one-dimensional signals is,

$$E = -\frac{1}{2}\mathbf{v}_\mathbf{y}^\mathbf{T}\mathbf{M}\mathbf{v}_\mathbf{y} - \mathbf{v}_\mathbf{y}^\mathbf{T}\mathbf{d}, \qquad (7)$$

where v_y is the output of a neuron. Note that the cellular neural network [6] is the 2-dimensional paradigm for image processing, while compact neural network is an effective architecture for 1-dimensional signal processing in communication. Due to the similarity between (6) and (7), linear mapping technique is applied. The output of a compact neural network will be the desired estimate $\hat{\mathbf{b}}$ if

$$\mathrm{M} = -\mathrm{H} \quad \text{and} \quad \mathrm{d} = \mathrm{y}. \qquad (8)$$

It means: if the synapse weight matrix M is equal to –H and the matched filters is followed by a compact neural network with the set synapse weight matrix, then the desired estimate $\hat{\mathbf{b}}$ can be obtained at the output of the compact neural network. Figure 3 shows the functional block diagram of a compact neural network based CDMA detector. Figure 4 shows the architecture of compact neural network core.

3 Gradient-Descent Optimization and Hardware Annealing

To achieve better performance for detection, optimization technique can be used. If a constraint energy is added to the original energy function of a compact neural network, the resultant energy function will be changed from convex to concave. The constraint energy function is

$$E_c = \mu \sum_{k=1}^{K} (v_{yk}^2 - 1) = \mu(\mathbf{v_y} + \mathbf{w_u})^T(\mathbf{v_y} - \mathbf{w_u}), \qquad (9)$$

where $\mathbf{w_u}$ is a 2K x 1 unit vector. If we discard-the constant term and use a fixed μ, then the matrix M = –H – 2μI is positive definite. Parameter μ controls the shape of energy landscape. If $\mu < -\lambda_{max}/2$ where λ_{max} is the maximum eigenvalue of the matrix H, the saturated binary output in the steady state is guaranteed. Due to the variations of the signal power from different users and the correlation between the signature waveforms, the exact eigenvalues are difficult to determine. However, the upper bound of eigenvalues of H can be estimated by adding some elements in the matrix H and use it to determine the proper μ value.

To escape from a large number of local minima, a novel optimization technique, hardware annealing [4] [5], is employeyed. The hardware annealing is performed by *continuously* controlling the gain $g(t)$ of the neuron from an initially small and positive value, $0 < \epsilon \leq g(0) << 1$ at $t = 0$, to the maximum gain $g_{max} = 1$ at $T_A < t \leq T_C$, during which the network is stablized.

The neuron transfer function can be described by

$$\begin{aligned} v_{yij}(t) &= f(g(t)v_{xij}(t)) \\ &= \begin{cases} +1 & ; gv_{xij} \geq 1 \\ gv_{xij} & ; -1 < gv_{xij} < 1 \\ -1 & ; gv_{xij} \leq -1. \end{cases} \end{aligned} \qquad (10)$$

4 Simulation Results

In this section, the performance of the conventional detector and that of the compact neural network based CDMA receiver are compared. Consider a $K = 2$ synchronous and noiseless case. The original transmitted signal is $b_{sent} = [-1, -1]^T$ at a given time. The near-far ratio r_{nf} is defined as

$$r_{nf} = \frac{\int s_i^2 dt}{\int s_j^2 dt} \tag{11}$$

and the normalized cross correlation of signature waveforms h is defined as

$$h = \frac{\int s_i s_j dt}{\sqrt{\int s_i^2 dt \int s_j^2 dt}}. \tag{12}$$

Therefore, H in (3) can be written as

$$\mathbf{H} = \begin{bmatrix} r_{nf}^{1/2} & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & h \\ h & 1 \end{bmatrix} \begin{bmatrix} r_{nf}^{1/2} & 0 \\ 0 & 1 \end{bmatrix}. \tag{13}$$

The normalized cross correlation of the users' signatures is h. The output of the matched filters y is sent to the neuron core for detection. The failure points (FPs) were recorded. Figures 5 and 6 show the distribution of failure points. Each failure point is determined if $b_{detected} \neq b_{sent}$. The result of OMD is obtained by full search as the reference method. The simulation range for the near-far ratio r_{nf} is $r_{nf} = [10^{-1}, \cdots, 10^{0.01}, 10^{0.02}, \cdots, 10]$ and the range for the correlation function h is $h =$ [-0.9, -0.89,-0.88,...,)].

The constraint energy function was not used in the simulation results as shown in Figure 5. Simulation results which include the constraint energy function are shown in Figure 6. The compact neural network based CDMA detectors fewer less failure points than the conventional detector. Because there are self-feedback connections in compact neural net works, the failure point distributions of upper sides, i.e., $r_{nf} > 1$, and lower sides are not same. In Figure 7, signals corrupted by neighboring user's interefrence and Gaussian noise were considered. The signal-to-noise ratio for user 1 is fixed at 10 dB. The compact neural net work based CD M A receiver with piecewise linear function was employed. Notice that a compact neural network based CDMA receiver could have better performance than optimal multiuser detector in the noise-corrupted cases. Simulation data were obtained for 10,000 cases.

5 Summary

A compact neural network based CDMA detector with robust near-far resistance is presented. The performance of the proposed neural network receiver is much better than that of the conventional detector. The addition of the constraint energy and the use of hardware annealing can significantly improve the detection performance. Further study will explore how to apply this technique to the downlink system in mobile handsets or PCS.

Acknowledgment

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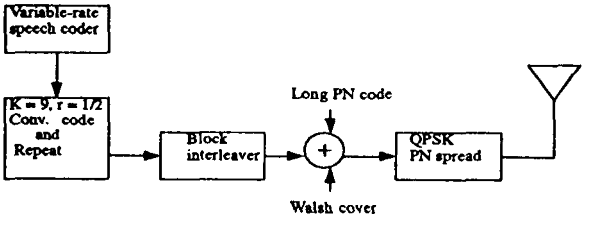

Figure 1: Block diagram of uplink in IS-95.

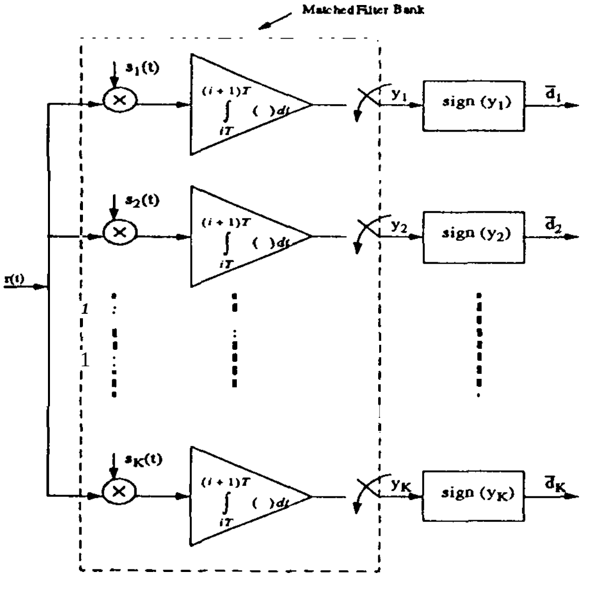

Figure 2: Conventional detector.

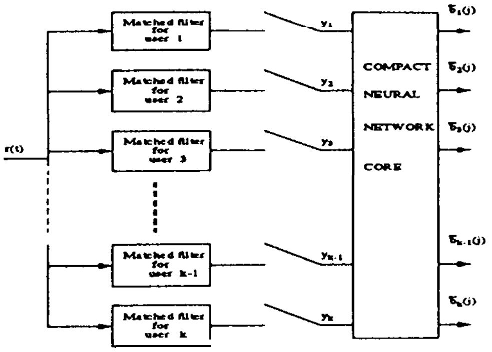

Figure 3: Functional block diagram of compact NN based CDMA detector.

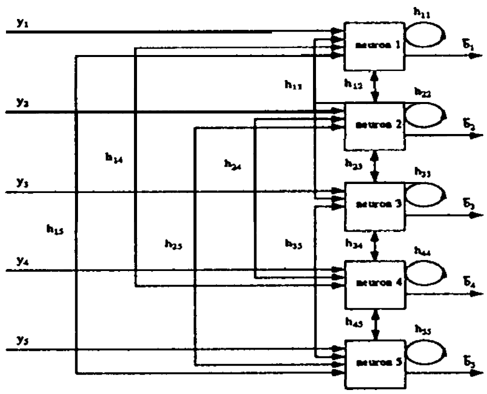

Figure 4: Architecture of compact NN core in CDMA detector (K=5).

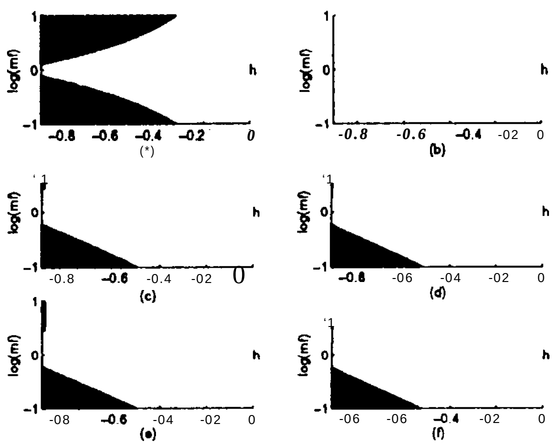

Figure 5: Distribution of failure points. Constraint energy function is not used. (a) Conventional detector. (b) Optimal multiuser detector. (c) Compact NN based CDMA detector with sigmoid function. (d) Compact NN based CDMA detector with sigmoid function and hardware annealing. (e) Compact NN based CDMA detector with piecewise linear function. (f) Compact NN based CDMA detector with piecewise linear function and hardware annealing.

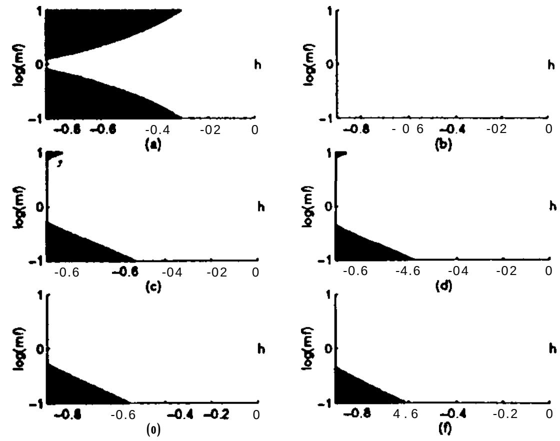

Figure 6: Distribution of failure points. Constranit energy function is applied. Conditions (a) to (f) are the same as Figure 5.

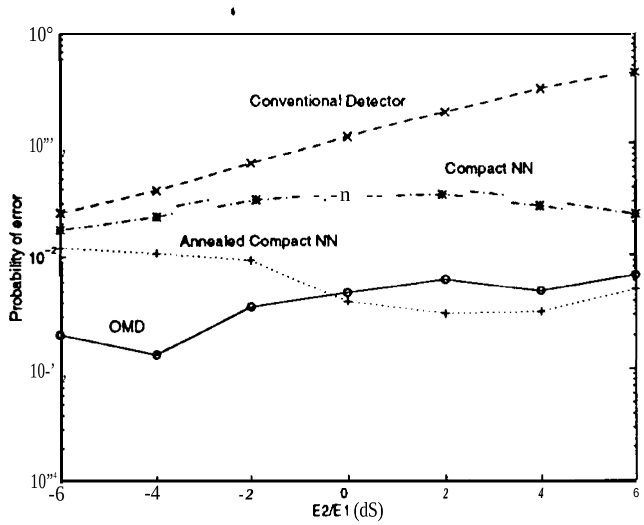

Figure 7: Error probability of conventional detector, compact NN based CDMA detectors and OMD. Signal-to-noise ratio for user 1 is fixed at 8dB.