RBF-Based Multiuser Detection for a Multirate DS/CDMA System

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ABSTRACT

In this paper, the RBF-based multiuser detector (MUD) is proposed for a multirate DS/CDMA system. The performance of RBF-based MUD is compared with that of many suboptimal multiuser detectors in terms of bit error probability. From the simulation results, it is confirmed that the RBF-based multiuser detector outperforms decorrelating detector, and achieves near-optimum performance in several situations. The results in this paper can be applied to design of MUD for a multirate DS/CDMA system.

I. INTRODUCTION

DS/CDMA (direct-sequence/code-division-multiple-access) is a promising multiple access technique for mobile and personal communication systems due to its anti-interference, random access capability, and soft capacity, etc. In a DS/CDMA system, multiple users are allowed to share a common channel to transmit information data bits. The target receiver can recover the information bits carried by known signature sequence by treating other user's signals as multiple access interference (MAI). The CDMA system performance may be degraded when the MAI becomes strong. The MAI from high-power users can significantly corrupt the received signals of low-power users, which is known as "near-far problem."

To overcome the near-far problem, concept of multiuser detection has been proposed by Verdu [1]. He proposed optimum multiuser detector to achieve the minimum bit error probability in AWGN channel, however, its complexity is on the order of $o(2^K)$ for K active users. The optimum multiuser detector (MUD) is basically maximum likelihood sequence detector consisting of a bank of matched filters followed by a Viterbi algorithm. To avoid prohibitive computational complexity of the optimum MUD, many suboptimal multiuser detectors have been proposed [2-6]. The suboptimal detectors include decorrelating detector, multistage detector, neural-network based detector, successive interference cancellation (SIC) detector, parallel interference cancellation detector (PIC) detector, adaptive detector, and iterative detector etc. Among them, we concentrate on the neural-network based multiuser detector in this paper.

Neural networks are highly interconnected networks of relatively simple processing units (called perceptron or node) that operate in parallel, so it can provide high computational processing with simple nonlinear processors [7]. Due to its massive parallelism and robustness, it has been applied to many kinds of problems such as pattern recognition, speech recognition, equalization, multiuser detection, and cellular network, etc [8-10].

The neural network can be largely classified into two categories: multilayer perceptron (MLP) neural network and recurrent neural network. The MLP-based multiuser detector has been proposed by Aazhang [11]. It has been shown that the MLP-based multiuser detector outperforms the conventional detector and the performance is par with the optimum multiuser detector. However, the MLP-based MUD suffers from slow convergence and unpredictable solutions during training period. Moreover, there exists a difficulty in setting the parameters of the MLP. Recently, radial basis function (RBF) network has attracted considerable attention in the neural network community [12-14]. The RBF is a kind of approaches of curve-fitting interpolation in multidimensional space, and its structure is identical to the optimal Bayesian solution [13].

The recent progress in the MUD is actively involved in development of efficient MUD for multirate data transmission [15]. In the previous research on neural network approach to multiuser detection, they have focused on the single rate (voice) transmission through CDMA channels [11,12]. There has not been any RBF-based approach for multiuser detection to multirate DS/CDMA systems. In this paper, the RBF-based multiuser detector is proposed for a multirate DS/CDMA system. The performance of RBF-based MUD is compared with that of many suboptimal multiuser detectors in terms of bit error probability. From the simulation results, it is confirmed that the RBF-based multiuser detector outperforms the other suboptimal detectors and achieves near-optimum performance in several situations.

The rest of the paper is organized as follows: In Section II, radial basis function and system models are described. In Section

III, the RBF processing is described. In Section IV, simulation results are presented and, finally, the conclusions are drawn in Section V.

II. SYSTEM DESCRIPTION

II. 1. *Transmitter and Receiver Model*

To achieve a multirate scheme for a DS/CDMA system, multicode DS/CDMA system has been proposed [16]. This system allows the user to transmit over one or several parallel code channels according to the data rate. The user transmits information bits employing several spreading sequences. The transmitter model for the multicode DS/CDMA system is shown in Fig. 1. The input data stream is first serial-to-parallel converted into N code channels, and data bit sequence in each code channel is spread by spreading sequence. The outputs from each code channel are summed, and then transmitted. The receiver model for the multicode DS/CDMA system is shown in Fig. 2. The received signal is processed at the matched filter (MF) bank of each user to despread signals of each code channel. The output of MF bank is parallel-to-serial converted, and sampled at chip rate. The output of chip rate sampler is processed at a radial basis function processor to estimate the transmitted data bits.

II. 2. Radial Basis Function

The RBF network has been successfully applied to the channel equalization and multiuser detection. As shown in Fig. 3, the RBF network typically consists of three layers: input layer, hidden layer, and output layer. The transformation from the input layer to the hidden layer is nonlinear, while the mapping from the hidden layer to the output layer is linear. The hidden layer's activation functions modify themselves slowly in accordance with some nonlinear optimization strategy. On the other hand, in the output layer, the weights change rapidly by some linear optimization method.

In the hidden layer, many algorithms such as generic algorithm, orthogonal least squares algorithm, and competitive learning (CL) algorithm have been proposed while in the output layer, stochastic descent algorithm such as LMS (least mean square) has been considered. The important system parameters in constructing the RBF network include weight, center, and spread parameter as well as basis function.

III. SYSTEM MODELING

III. 1. Multicode DS/CDMA Modeling

The transmitted signal of the *kth* user is given by

$$s_k(t) = \sum_{i=1}^{N} \sqrt{2P_{k,i}}\, d_{k,i}(t) c_{k,i}(t) \cos(\omega_c t + \theta_{k,i}), \quad (1)$$

where N is the number of code branch, $P_{k,i}$ is signal power, $d_{k,i}(t)$ is data sequence with bit duration T_b, $c_{k,i}(t)$ is spreading sequence with chip duration T_c, ω_c is carrier frequency, and $\theta_{k,i}$ random carrier phase. Then, the received signal from K users in an AWGN channel is given by

$$r(t) = \sum_{k=1}^{K} s_k(t-\tau_k) + n(t), \quad (2)$$

where τ_k is propagation delay.

III. 2. RBF Processing

Each hidden layer unit produces norm distance (typically, Euclidean distance) between its own center $\mathbf{C}_i (1 \le i \le N)$ and the RBF input $\mathbf{X}_i (1 \le i \le N)$. The norm distance is then divided by a center spread parameter, and the result is passed through a nonlinear function ϕ. The output of the RBF network is given by

$$F(\mathbf{X}) = \sum_{i=1}^{N} w_i \phi(\|\mathbf{X} - \mathbf{C}_i\| / \sigma_i^2), \quad (3)$$

where $\phi(\cdot)$ is a nonlinear basis function, w_i is output layer weight, $\mathbf{C}_i$ is center, and σ_i is center spread parameter. We have many choices for the nonlinear function $\phi(\cdot)$. This nonlinear basis function typically includes Gaussian function, thin-plate-spline function, and multiquadratic function with their respective representations,

$$\phi(x) = \exp(-\frac{x^2}{2\sigma^2}), \quad (4)$$

$$\phi(x) = x^2 \log x \text{, and} \quad (5)$$

$$\phi(x) = \sqrt{x^2 + \sigma^2}. \quad (6)$$

IV. SIMULATION RESULTS

For simulation examples, it is assumed that BPSK modulation is used for data and chip sequences, and chip synchronization is perfectly achieved. The relative propagation delay of all users is set to be zero to simulate synchronous operation of the system. The spreading sequences for all users are chosen from a set of Gold codes of length of 31. To obtain the centers of the hidden layer, the CL algorithm as an adaptive version of the *k-means* algorithm is used. In the CL algorithm, all the center vectors compete with each other. The center vector with the minimum difference from the input vector is selected as a winner.

In Fig. 4, we compare bit error probability of the RBF-based MUD and the optimum and conventional schemes with the number of users $K = 6$ and Gaussian nonlinear basis function, under perfect power control. The RBF-based MUD achieves almost the same bit error probability as the optimum MUD over the wide range of SNR. And, its BER performance is superior to the decorrelating MUD.

In Fig. 5, bit error probability vs. NFR (near-far ratio) is shown with SNR (of reference user) of 6dB, Gaussian nonlinear basis function, and the number of users $K = 6$, under near-far situation. The NFR is defined as ratio between an interferer's received power and the received power of the reference user. As seen in Fig. 5, the RBF-based MUD is robust against the near-far problem, and its BER performance approaches the optimum MUD. The bit error probability of the MF detector increases rapidly as the NFR because the MF detector employs single-user detection strategy, i.e., it ignores the MAI in the detection process.

In Fig. 6, we investigate the effect of selection of nonlinear basis function ϕ with SNR (of reference user) of 6dB and the number of users $K = 6$ under near-far situation. Over the wide range of the NFR, the Gaussian nonlinear function slightly outperforms the thin-plate-spline and the multi-quadratic nonlinear basis functions.

V. CONCLUSIONS

The performance of the RBF-based MUD is proposed and simulated for a multirate DS/CDMA system. From the simulation results, it is shown that the RBF-based MUD outperforms the decorrelating detector, and achieves near-optimum performance in several situations. The results of this paper can be applied to design of MUD for a multirate DS/CDMA system.

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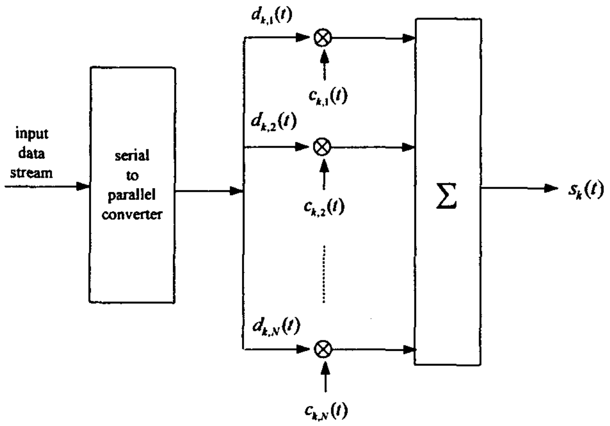

Fig. 1. Transmitter model of the *kth* user of a multicode DS/CDMA system.

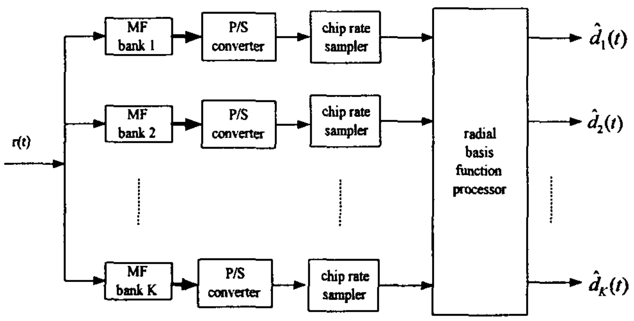

Fig. 2. Receiver model for a multicode DS/CDMA system.

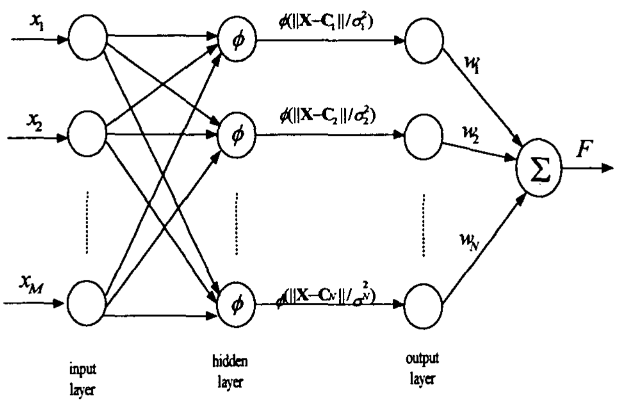

Fig. 3. Schematic diagram of radial basis function network.

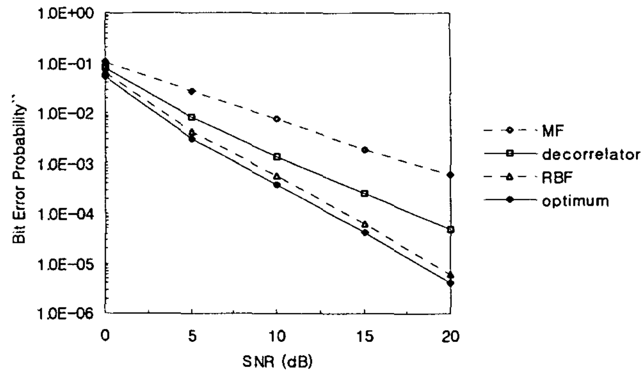

Fig. 4. Bit error probability with perfect power control.

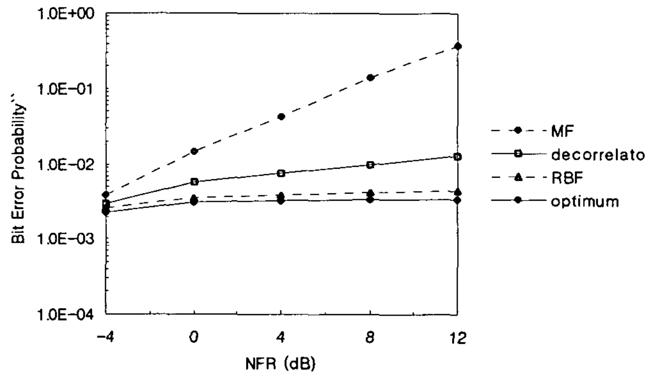

Fig. 5. Bit error probability with near-far situation.

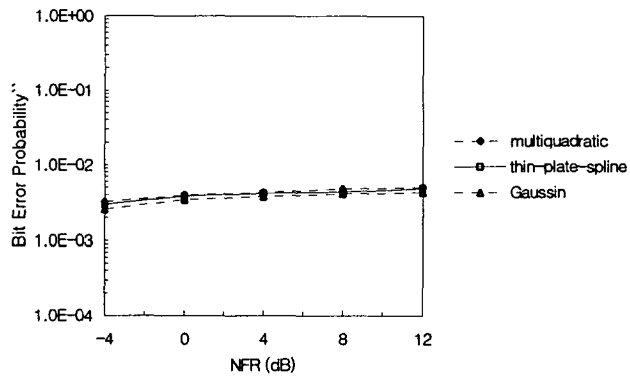

Fig. 6. Effect of nonlinear basis function on BER performance.