

Reduced RBF Centers Based Multiuser Detection in DS-CDMA System

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ABSTRACT

The major goal of this paper is to develop a practically implemental radial basis function (RBF) neural network based multi-user detector (MUD) for direct sequence (DS)-CDMA system. This work is expected to provide an efficient solution for RBF based MUD by quickly setting up the proper number of RBF centers and their locations required in training. The basic idea in this research is to estimate all the possible RBF centers by using supervised k -means clustering technique, and select the only centers which locate near seemingly decision boundary between centers, and reduce further by grouping the some of centers adjacent each other. Therefore, it reduces the computational burden for finding the proper number of RBF centers and their locations in the existing RBF based MUD, and ultimately, make its implementation practical.

Key Words : Multiuser, Detector, DS-CDMA, RBF, Neural Network

I. Introduction

A critical issue for future wireless communications systems is the selection of proper multiple access techniques for reliable and affordable communication, anywhere and anytime. One type of wireless technology which has become popular over the last few years is the direct-sequences code division multiple access (DS-CDMA). DS-CDMA uses spread spectrum modulation so that the narrow band signals of each user look like low power wideband noise to all other users. In a DS-CDMA system, the objective of the receiver is to detect the transmitted information bits of one (at mobile-end) or many (at base station) users.

1.1 Background

A variety of MUD has been proposed for DS-CDMA systems. Generally, the linear minimum mean square error (MMSE) MUD is widely

used, as it is computationally very simple and can readily be implemented using standard adaptive filter techniques^[1-3]. The conventional linear detectors, however, fail to achieve good performance when channel suffers from high levels of additive noise or highly nonlinear distortion, or when the signal-to-noise ratio is poor. The linear detector can only work when the underlying noise-free signal classes are linearly separable with the introduction of proper channel delays, where the channel is assumed to be stationary. In reality, the mobile channels are going to be non-stationary where it is hard to determine the proper channel delay that varies with time. If proper channel delay is not introduced in linear MUD, the signal classes from the channel output states will be non-linearly separable.

In order to get around this problem, neural network technology has been considered in implementing MUD, because it has the capability of recovering the originally transmitted signals from

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nonlinear decision boundary cases^[4-8]. In fact, neural networks have received much attention from a variety of fields, especially for telecommunication systems, because of its characteristics, such as inherent parallelism, noise immunity, knowledge storage, adaptability, and pattern classification capability^[4-13].

Aazhang et al.^[4] first reported a study of multi-layer perceptrons (MLP) in CDMA systems, and showed that its performance is close to that of the optimum receiver in both synchronous and asynchronous Gaussian channels. Although the simulation results proved that back-propagation learning rule outperforms the conventional one, it still leaves a lot of difficulties, such as long training time, performance sensitivity over network parameters including initial weights, and finding the proper number of hidden layer and hidden nodes. In [5], it is shown that the energy function of the recurrent neural network is identical to the likelihood function encountered in MUD. The dynamics of the network are geared toward minimization of a energy function. The performance of the receiver is near optimum; however, the receiver is non-adaptive.

For the last decade, radial basis functions (RBF) neural network have been the promising candidate for the application to various telecommunication fields, including channel equalization and detection^{[6][7][10-13]}. Mitra and Poor^[6] applied a RBF network to the MUD problem. The simulation results show that the RBF based MUD is its intimate link with the optimal one-shot detector, and its training times are better and more predictable than the MLP. However, the RBF based MUD obviously requires more RBF centers, when both channel order and the number of users increase. Eventually, it leads to computational complexity. Thus, it becomes necessary to determine the proper number of RBF centers for the practically implemental RBF based MUD. In [15], Chen et al. employed support vector machine for MUD. It still has difficulty of finding proper number of support vectors or reducing them.

1.2 RBF Neural Network

Originally, RBF network was developed for data interpolation in multi-dimensional space^[14]. The RBF is becoming an increasingly popular neural network with diverse application and is probably the main competitor to the ML. Much of the inspiration for RBF networks has come from the traditional statistical pattern classification technique.

A RBF network is a three-layer network whose output nodes form a linear combination of the basis (or Kernel) functions computed by the hidden layer nodes. The basis functions in the hidden layer produce a localized response to input stimuli. A diagram of a radial basis function network is shown in Figure 1.

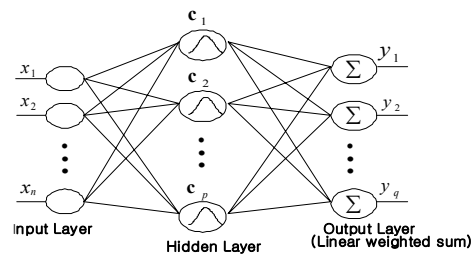


Fig. 1 Block diagram of RBF neural networks

1.3 Proposed Techniques

As mentioned above, neural network based MUD has shown great promises over linear ones, such as adaptability for nonlinear separable problem and better error performance^{[4][16]}. However, MLP based MUD requires long training time and risks getting stuck to the local minima due to the initial training weights^[4]. On the other hand, the RBF based MUD has some advantages over MLP based MUD, such as structural simplicity, fast training, and better error performance. It, however, still results in higher computational complexity, when both channel order and the number of users go high; more RBF centers are required as the channel order increases^{[6][7]}. This increase of centers will lead to the long training. Furthermore, the optimal number of RBF centers and the position of RBF centers should be determined before training.

The main purpose of this paper is to develop a technique for quickly determining the number of RBF centers and their location, and to apply the RBF neural network with the proposed techniques to the multi-user detection problem. The basic idea behind the proposed techniques is to select the centers which locate near the decision boundary. Furthermore, the selected RBF centers will be averaged especially when the distribution of RBF centers are dense.

II. RBF based Multiuser Detector

Fig. 2 shows the baseband model of a RBF based synchronous DS-CDMA communication supporting N users with M chips. The data bit $s_{i,k} \in \{\pm 1\}$ denotes the symbol of user i at time k , which is multiplied by the spreading, or signature waveform where u_i is the chip wave form

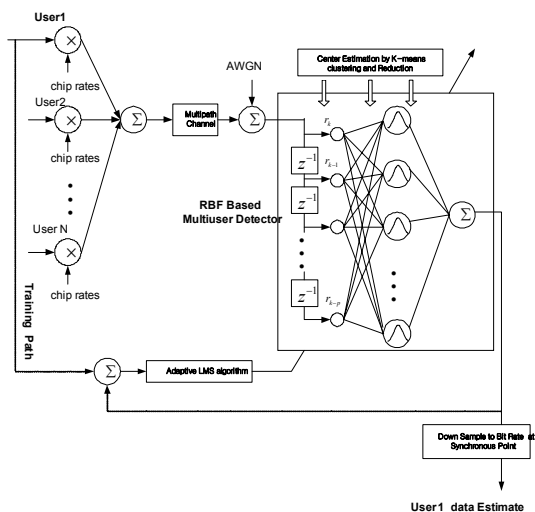


Fig. 2 Structure of RBF based MUD

with unit energy. The signature sequence for user i is represented as

$$\mathbf{u}_i = [u_{i,1}, \dots, u_{i,M}]^T \quad (1)$$

and the channel impulse response is

$$H(z) = h_0 + h_1 z^{-1} + \dots + h_q z^{-q} \quad (2)$$

where q denotes the channel order. The baseband model for received signal sampled at chip rate is represented as^[16]

$$\mathbf{r}_k = \begin{bmatrix} h_0 & h_1 & \dots & h_q \\ & h_0 & h_1 & \dots & h_q \\ & & \dots & & \\ & & & h_0 & h_1 & \dots & h_q \end{bmatrix} \begin{bmatrix} \mathbf{U}\mathbf{A} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{U}\mathbf{A} & & \\ \vdots & & \mathbf{U}\mathbf{A} & \mathbf{0} \\ \mathbf{0} & \dots & \mathbf{0} & \mathbf{U}\mathbf{A} \end{bmatrix} \begin{bmatrix} \mathbf{S}_k \\ \mathbf{S}_{k-1} \\ \vdots \\ \mathbf{S}_{k-P+1} \end{bmatrix} + \mathbf{n}_k \quad (3)$$

$$= \hat{\mathbf{r}}_k + \mathbf{n}_k$$

where the user symbol vector $\mathbf{S}_k = [s_{1,k}, s_{2,k}, \dots, s_{N,k}]^T$, the white Gaussian noise vector $\mathbf{n}_k = [n_{1,k}, \dots, n_{M,k}]^T$, $\hat{\mathbf{r}}_k$ denotes the noise free received signal. The first, second, and third part of \mathbf{r}_k are $M \times PM$ channel impulse response matrix, $PM \times PN$, and $PN \times 1$, respectively. Thus, the \mathbf{r}_k is the $M \times 1$ vector. $\mathbf{U} = [u_1, \dots, u_N]$ denotes the normalized user code matrix, and the diagonal user signal amplitude matrix is given by $\mathbf{A} = \text{diag}\{A_1, \dots, A_N\}$. The channel inter-symbol interference span P depends on the channel order q and the chip sequence length M [16]: $P = 1$ for $q = 0$, $P = 2$ for $0 < q \leq M - 1$, $P = 3$ for $M - 1 < q \leq 2M - 1$ and so on.

2.1 Adaptive Training of RBF MUD

Considering the third part in (3), the user symbol vectors, \mathbf{S}_k , the number of user, N and the number of interference span, P , there are 2^{NP} combinations of the channel input sequence. Here, \mathbf{S}_k is represented as

$$\mathbf{S}_k = [s_{1,k}, s_{2,k}, \dots, s_{N,k}, s_{1,k-1}, s_{2,k-1}, \dots, s_{N,k-1}, \dots, s_{1,k-P+1}, s_{2,k-P+1}, \dots, s_{N,k-P+1}]^T \quad (4)$$

This produces 2^{NP} values of the noise-free channel output vector

$$\mathbf{r}_k = [r_k, r_{k-1}, \dots, r_{k-M+1}]^T \quad (5)$$

These vectors will be referred to as the desired channel states (used as RBF centers), and they can be partitioned into two classes according to the corresponding value in S_i , depending on which user is considered in making decision (here no channel delay is assumed

$$\begin{aligned} R_i^+ &= \{\hat{r}_k | S_{i,k} = 1\}, \\ R_i^- &= \{\hat{r}_k | S_{i,k} = -1\}, \end{aligned} \quad (6)$$

Once all the channel output states and corresponding desired state are determined, these values can be used as training pairs (input output) for training RBF based multi-user detector. The output response of an RBF network is a mapping F

$$F(\mathbf{r}) = \sum_{i=1}^n w_i \exp\left(-\|\mathbf{r} - \mathbf{c}_i\|^2 / 2\sigma^2\right) \quad (7)$$

where n is the number of RBF centers selected for training, w_i are output layer weights, the \mathbf{c}_i are basis function center vectors, and the σ^2 is the basis function spread parameter. RBF centers used in training are estimated by hiring the supervised k -means clustering algorithm^[10] and the weights are adaptively updated using the supervised least mean square (LMS) algorithm.

2.2 Center Reduction for Fast Learning

As mentioned before, determining the number and location of centers is a difficult part of design. By the theory^[10], the number of all the possible RBF centers doubles for each increase in channel order and each increase in user number, the computational complexity increases exponentially. This work used algorithms previously proposed in the research^{[12][13]}. The approach to reducing the number of centers relies on selecting only centers close to the decision boundary. The following is a procedure for selecting and reducing the RBF centers required in training.

Algorithm:

Step 1: Estimate n number of RBF centers using supervised k -means clustering^[10]

$$\begin{aligned} & \text{if}(S_k = S_i) \{ \\ & \mathbf{c}_{i,k} = \text{counter}_i * \mathbf{c}_{i,k-1} + \mathbf{r}_i; \\ & \text{counter}_i = \text{counter}_i + 1; \\ & \mathbf{c}_{i,k} = \mathbf{c}_{i,k} / \text{counter}_i \\ & \} \end{aligned}$$

Step 2: Sort the estimated centers in ascending order, based on the combination number of binary signals as shown in equation (4). Determine each group of centers. $Center^j, j = 1, 2, \dots, 2^q$ with the following procedure.

$$Center^n : \left\{ \begin{array}{l} \text{Center index number for the first half} \\ n, n+2^q, \dots, (M/2 - (n-1)) - 2^q, M/2 - (n-1) \end{array} \right\}$$

$$\left\{ \begin{array}{l} \text{Center index number for the second half} \\ n+M/2, n+2^q+M/2, \dots, (M/2 - (n-1)) - 2^q + M/2, M/2 - (n-1) + M/2 \end{array} \right\}$$

Step 3: Find the center category J , for which the maximum value of each center group, $Center^j$, is smaller than the values of other center groups.

$$J = \arg \left[\text{Min } C_{\max}^j \right], j = 1, 2, \dots, 2^q$$

where C_{\max}^j represents the maximum value of center among all the centers in $Center^j$. This step is for selecting only the centers which are close to decision boundary.

Step 4: Find all the centers in $Center^J$.

Step 5: Sort the selected centers in ascending order based on the combination number of the associated binary signals, and set $\mathbf{c}_i^j, i = 1, \dots, L$, as a set of ordered centers, where $L = M / 2^q = 2^{np-q}$.

Step 6: Find all the average distance (AD) between the +1 centers and -1 centers through step below; here +1 centers stands for the center whose corresponding received symbol of i th user, $S_{j,k}$ is equal to 1, while -1 centers stands for the

center whose corresponding received symbol of i th user $S_{j,i}$ is equal to -1.

$$\begin{aligned} & \text{for}(l=1;l \leq L/4; ++l)\{ \\ & \quad AD = AD + f_{abs}(c^l - c^{2^{l-(l-1)}}) \\ & \} \\ & AD = AD/(L/4) \end{aligned}$$

Step 7: Check if $(AD \geq \gamma)$, where γ is a distance parameter in the range $0.5 \leq \gamma \leq 1.0$ used to keep the centers properly separated without overlapping (severe intersymbol interference causes the regions containing +1 and -1 centers to overlap).

If NOT, then the current candidate category is rejected; return to Step3.

If YES, stop (all the centers in category J will be used for network training).

Step 8: To deal with the channel, whose order is high enough to make the distribution of channel output states very dense, an additional step is taken. The method is to group 2^ρ numbers of consecutive centers, after sorting the centers in step 2 based on their combinations of user symbol signals as shown in equation (4), where ρ is arbitrary number that could increase or decrease due to the status of channel output distribution.

III. Simulation Studies

Simulation studies were performed to compare RBF based MUD with and without reduction in the number of RBF centers. For the purpose of showing that multiuser detection can be regarded as a classification problem, a very simple two user system with 2 chips per symbol was considered. The chip sequences of the two users were set as (-1, -1) and (-1, 1), respectively. The following are channel impulse responses used in simulation

$$\left. \begin{aligned} H_1(z) &= 1 + 0.4z^{-1} \\ H_2(z) &= 0.8 + 0.5z^{-1} + 0.3z^{-2} \end{aligned} \right\} \quad (8)$$

The two users are assumed to have equal signal power. Simulation works consist of some procedures. The first is to estimate both the RBF

centers and noise variances using supervised k -means clustering^[10]. The next one is to select only the estimated centers which are close to decision boundary^[13]. The center spread value was set to $2\sigma^2$ where σ^2 is the same as estimated noise variance. Once the RBF centers and center spreads are determined, weights updating begins using adaptive LMS algorithm. The learning rate used in training was between 0.01 and 0.05. The number of training samples was 20,000. The bit error rate (BER) performance was conducted with 100,000 inputs with Gaussian noise. The estimated centers shown in Fig. 3(a) are well separated, and the number of centers was reduced from 16 (only 12 points are shown in graph, because some of centers have same values) to 4 using a technique^[13]. As shown in Fig. 4(a), the error rate performance of an RBF based MUD with reduction in centers compared favorably with the RBF based MUD without reduction in centers, and better than a linear MUD. Fig. 3(b) illustrates both the selected centers and averaged centers. Fig. 4(b) shows that RBF based MUD with reduction in centers performed as well as the RBF based MUD without center reduction.

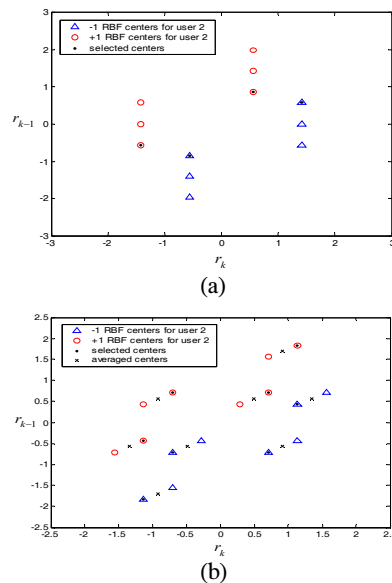


Fig. 3 Distribution of selected centers

$$\begin{aligned} \text{(a)} & H(z) = 1 + 0.4z^{-1} \\ \text{(b)} & H(z) = 0.8 + 0.5z^{-1} + 0.3z^{-2} \end{aligned}$$

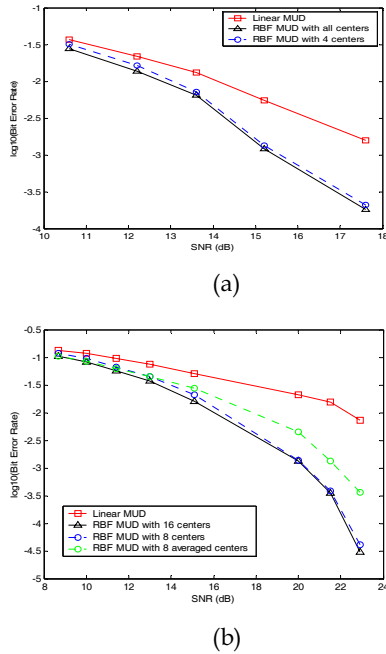


Fig. 4 Comparison of error rate performance

(a) $H(z) = 1 + 0.4z^{-1}$
 (b) $H(z) = 0.8 + 0.5z^{-1} + 0.3z^{-2}$

IV. Conclusion

The RBF based multiuser detector (MUD) described in this paper was developed primarily for overcoming the difficulties of using a large number of centers in RBF based MUD, especially when channel order and user number go to high.

RBF based MUD with and without reduction in the number of centers performed better than the linear multi-user detector, and error rate performance of the RBF based MUD with reduction in the number of centers was comparable, in most cases, to performance with the full number of centers. These improvements in RBF based MUD design could make its implementation more practical.

Research has been continuing into more complex cases with higher channel order, many users, and long chip sequences. It is expected that the results of this study can be extended to various wireless cellular communication systems using multiple access schemes such as DS-CDMA, OFDM-CDMA, and multi-carrier CDMA.

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