Reduced RBF Centers Based Multiuser Detection in DS-CDMA System

Jung-Sik Lee*, Jae-Jeong Hwang*, Chi-Yeon Park** ***Regular Members***

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

※ This work was financially supported by the Kunsan National University's Long-term Overseas Research Program for Faculty Member in the year 2004.
* School of Electronics & Information Eng., Kunsan National University ({leejs,hwang}@kunsan.ac.kr)
** Dept. of Computer Science & Eng., Kwandong University (cypark@kwandong.ac.kr)
논문번호 : KICS2006-06-263, 접수일자 : 2006년 6월 8일, 최종논문접수일자 : 2006년 11월 8일

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.

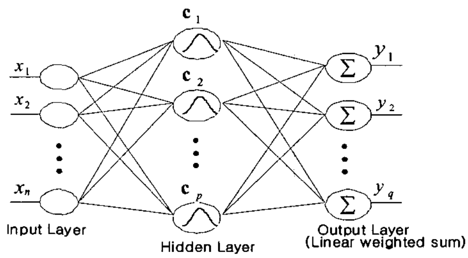


Fig. 1 Block diagram of RBF neural networks

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

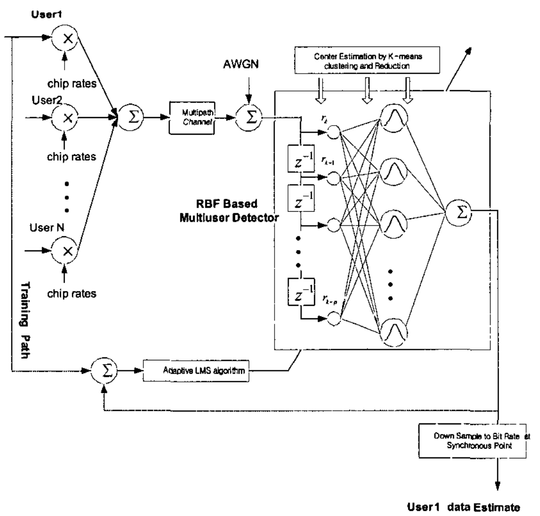


Fig. 2 Structure of RBF based MUD

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

$$\mathbf{u}_i = [u_{i,1}, \ . \ . \ . \ , u_{i,M}]^T \tag{1}$$

and the channel impulse response is

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

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

$$\mathbf{r}_k = \begin{bmatrix} h_0 & h_1 & \cdots & h_q & & & \\ & h_0 & h_1 & \cdots & h_q & & \\ & & & \cdots & & & \\ & & & & h_0 & h_1 & h_q \end{bmatrix} \begin{bmatrix} \mathrm{UA} & 0 & \cdots & 0 \\ 0 & \mathrm{UA} & \cdot & \cdot \\ \cdot & \cdot & \mathrm{UA} & 0 \\ 0 & \cdots & 0 & \mathrm{UA} \end{bmatrix} \begin{bmatrix} \mathbf{s}_k \\ \mathbf{s}_{k-1} \\ \cdot \\ \cdot \\ \mathbf{s}_{k-P+1} \end{bmatrix} + \mathbf{n}_k \tag{3}$$

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

where the user symbol vector $\mathbf{s}_k = [s_{1,k}, s_{2,k}, \ldots, s_{N,k}]^T$, the white Gaussian noise vector $\mathbf{n}_k = [n_{1,k}, \ldots, n_{M,k}]^T$, $\hat{\mathbf{r}}_k$ 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. $\mathrm{U} = [\mathbf{u}_1, \ldots, \mathbf{u}_N]$ denotes the normalized user code matrix, and the diagonal user signal amplitude matrix is given by $\mathrm{A} = diag\{A_1, \ldots, A_N\}$. 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 $0 < q \le M-1$, $P=3$ for, $M-1 < q \le 2M-1$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

$$\mathbf{s}_k = [s_{1,k}, s_{2,k}, \ldots, s_{N,k}, s_{1,k-1}, s_{2,k-1}, \ldots, s_{N,k-1}, \ldots, s_{1,k-P+1}, s_{2,k-P+1}, \ldots, s_{N,k-P+1}]^T \tag{4}$$

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

$$\mathbf{r}_k = [r_k, r_{k-1}, \ldots, r_{k-M+1}]^T \tag{5}$$

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 $\mathbf{s}_k$, depending on which user is considered in making decision (here no channel delay is assumed

$$\left.\begin{aligned} R_i^+ &= \{\hat{r}_k \mid s_{i,k} = 1\}, \\ R_i^- &= \{\hat{r}_k \mid s_{i,k} = -1\}, \end{aligned}\right\} \quad (6)$$

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]

$$\begin{aligned} & if(\mathbf{S}_k = \mathbf{S}_i)\{ \\ & \mathbf{c}_{i,k} = counter_i * \mathbf{c}_{i,k-1} + \mathbf{r}_k; \\ & counter_i = counter_i + 1; \\ & \mathbf{c}_{i,k} = \mathbf{c}_{i,k} / counter_i \\ & \} \end{aligned}$$

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. $Center^j, j = 1, 2, \ldots, 2^q$ with the following procedure.

$$Center^n : \left\{ \overbrace{n, n+2^q, \ldots, \left(M/2 - (n-1)\right) - 2^q,\ M/2 - (n-1)}^{\text{Center index number for the first half}} \right\}$$
$$\left\{ \overbrace{n + M/2, n + 2^q + M/2, \ldots, \left(M/2 - (n-1)\right) - 2^q + M/2,\ M/2 - (n-1) + M/2}^{\text{Center index number for the second half}} \right\}$$

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.

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

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 $\mathbf{c}_l^J, l = 1;,$ 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, $\mathbf{S}_{j,k}$ is equal to 1, while -1 centers stands for the center whose corresponding received symbol of i th user $s_{j,k}$ is equal to -1.

$for(l = 1; l \le L/4; ++l)\{$

$AD = AD + fabs\left(c^{l} - c^{2^{p}-(l-1)}\right)$

$\}$

$AD = AD/(L/4)$

Step 7: Check if $(AD \ge \gamma)$, where γ is a distance parameter in the range $0.5 \le \gamma \le 1.0$ 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).

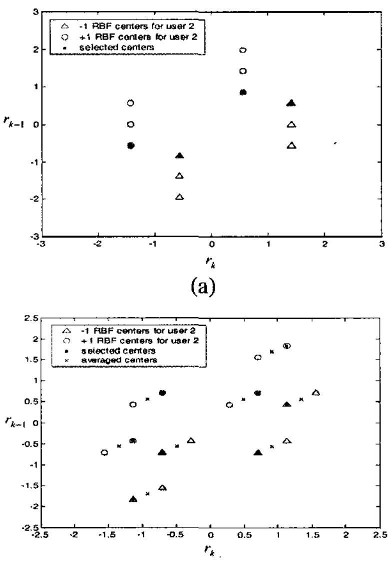
Step 8: To deal with the channel, whose order is high enough to make the distribution of channel output states very dense, an additional step is taken. The method is to group 2^{p} numbers of consecutive centers, after sorting the centers in step 2 based on their combinations of user symbol signals as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

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

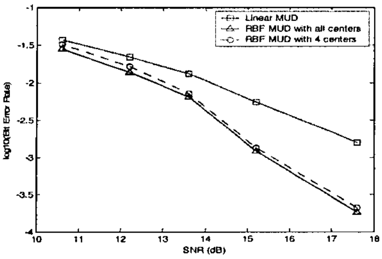
The two users are assumed to have equal signal power. Simulation works consist of some procedures. The first is to estimate both the RBF centers and noise variances using supervised k -means clustering[10]. The next one is to select only the estimated centers which are close to decision boundary[13]. 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.



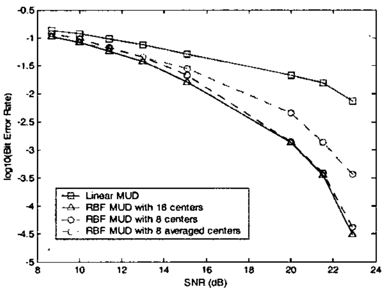
(a)

(b)

Fig. 3 Distribution of selected centers
(a) $H(z) = 1 + 0.4z^{-1}$
(b) $H(z) = 0.8 + 0.5z^{-1} + 0.3z^{-2}$



(a)



(b)

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.

References

〔1〕 Madhow, U., Honig, M. L., "MMSE Interference Suppression for Direct Sequence Spread Spectrum CDMA," IEEE Transactions on Communications, Vol. 42., pp. 3178-3188, 1994.

〔2〕 Miller, S. L., "An Adaptive Direct-Sequence Code-Division Multiple-Access Receiver for Multiuser Interference Rejection, "IEEE Transactions on Communications, Vol. 43, pp. 1746-1755, 1995.

〔3〕 Poor, H.V.,Verdu, S., "Probability of Errors in MMSE Multiuser Detection," IEEE Transactions on Information Theory, Vol. 43, pp. 858-871, 1997.

〔4〕 Aazhang, B., Paris, B.P., Orsak, G.C., "Neural Networks for Multiuser Detection in Code-Division Multiple-Access Channels," IEEE Transactions on Communications, Vol. 40, pp. 1212-1222, 1992.

〔5〕 Miyajima, T., Hasegawa, T., Haneishi, M., "On the Multiuser Detection using a Neural Network in Code-Division Multiple-Access Communications," IEICE Transactions on Communications, Vol. E76-B, pp. 7-11, 1993

〔6〕 Mitra, U., Poor, H.V., "Neural Network Techniques for Adaptive Multiuser Demodulation," IEEE Journal on Selected Areas in Communications, Vol. 12, pp. 1460-1470, 1994.

〔7〕 Cruickshank, D.G.M., "Radial Basis Function Receivers for DS-CDMA," IEE Electronic Letters, Vol. 32, pp. 188-190, 1996.

〔8〕 Matyjas, J.D., Psaromiligkos, I.N., Batalama, S.N., Medley, M.J., "Fast Converging Minimum Probability of Error Neural Network Receivers for DS-CDMA Communications," IEEE Transactions on Neural Networks, Vol. 15, pp. 445-454, 2004.

〔9〕 Gibson, G.J., Siu, S., Cowan, C.F.N., "Application of Multilayer Perceptrons as Adaptive Channel Equalizers," IEEE International Conference on Acoustics, Speech, Signal Processing, pp. 1183-1186, 1989.

[10] Chen, S., Mulgrew, B., Grant, P.M., "A Clustering Technique for Digital Communication Channel Equalization using Radial Basis Function Networks," IEEE Transactions on Neural Networks, Vol. 4, pp. 570-579, 1993.

[11] Lee, J.,Beach, C.D., Tepedelenlioglu, N., "Channel Equalization using Radial Basis Function Network," IEEE International Conference on Acoustics, Speech, Signal Processing, Vol. 3, pp. 1719-1722, 1996

[12] Lee, J., Beach, C.D., Tepedelenlioglu, N.," Channel Equalization using Radial Basis Function Network," IEEE International Conference on Neural Networks, Vol. 4, pp. 1924-1928, 1996.

[13] Lee, J., Beach, C.D., Tepedelenlioglu, N., "A Practical Radial Basis Function Equalizer," IEEE Transactions on Neural Networks, Vol. 10, pp. 450-455, 1999.

[14] Powell, M.J.D., "Radial Basis Functions for Multivariable Interpolation: a Review," Algorithm for Approximation, pp. 143-167, 1987.

[15] Chen, S., Samingan, A.K., Hanzo, L., "Support Vector Machine Multiuser Receiver for DS-CDMA Signals in Multipath Channels," IEEE Transactions on Neural Networks, Vol. 12, pp. 604-610, 2001.

[16] Chen, S., Samingan, A.K., Hanzo, L., "Adaptive Near Minimum Error Rate Training for Neural Networks with Application to Multiuser Detection in CDMA Communication Systems," Signal Processing , Vol. 85, pp. 1435-144, 2005.

이 정 식 (Jung-Sik Lee) 정회원

1983년 한양대학교 전자통신과 공학사
1990년 Florida Institute of Tech., Elec. Eng. M.S.
1996년 Florida Institute of Tech., Elec. Eng. Ph.D.
1986년~1988년 OPC 중앙연구소 연구원
2004년~2005년 Univ. Of South Florida 방문 교수
1997년~현재 군산대 전자정보공학부 부교수
<관심분야> 적응신호처리, 통신이론, 신경망

황 재 정 (Jae-Jeong Hwang) 정회원

1983년 전북대학교 전자공학과 졸업
1992년 전북대학교 대학원 전자공학과 공학박사
1993년 미국 텍사스주립대 객원교수
1992년~현재 군산대학교 전자정보공학부 교수
2003년 호주 모나쉬대학교 객원교수
저서 Techniques and standards for image, video, and audio coding, Prentice Hall, 1996.
<관심분야> 동영상부호화, 디지털방송 신호처리, 멀티미디어 통신, 디지털 통신

박 지 연 (Chi-Yeon Park) 정회원

1985년 경희대학교 기계공학과 공학사
1987년 Florida Institute. of Tech., Computer Science, M.S.
1996년 Florida Institute of Tech., Computer Science, Ph.D.
1989~1992년 LG-CNS 기술연구소 연구원
1996~1997년 삼성 SDS 연구소 책임연구원
1997~현재 관동대학교 컴퓨터공학과 부교수
<관심분야> 신경망, 최적화알고리즘, 지능형시스템