Short Paper

The Multi-User Detection in Code Division Multiple Access with Adaptive Neuro-Fuzzy Inference System

YALCIN ISIK AND NECMI TASPINAR*
Department of Electronics, Vocational High School
**Department of Electronic Engineering*
Erciyes University
38039 Kayseri, Turkey
E-mail: {isiky, taspinar}@erciyes.edu.tr

In this paper, multi user detection in Code Division Multiple Access (CDMA) was realized with an adaptive neuro-fuzzy inference system (ANFIS) and the bit error rate (BER) performance was compared with the performances of the matched filter and a neural network receiver. Increment of the number of the active users and the receiving various user signals at the receiver input stage in different power levels in CDMA degrade BER performance of the receiver. The receiver that used ANFIS has a better bit error rate (BER) performance than the neural network receiver's and the training process of the ANFIS is faster than the neural network's.

Keywords: CDMA, multi-user detection, adaptive neuro-fuzzy inference system, MAI (multiple access interference), near-far effect

1. INTRODUCTION

In the near future, wireless communication systems will be used not only for voice service but for several kinds of other communication services such as data, image, and video transmission, which inherently have different data rates and quality of service (QoS) requirements. CDMA system is attractive for these communication services. In a CDMA system, several of users simultaneously transmit information over a common channel using pre-assigned codes. The conventional matched filter detector consists of a bank of filters matched to the spreading codes. But, as the number of the active users increases in the system, this detector suffers multiple access interference (MAI) produced by the other co-channel users. This problem causes significant limitation to the capacity of this detector. Also when the relative received powers of interfering signals become larger, the near-far effect occurs at this detector. Mutually orthogonal spreading codes can be selected for all users to overcome MAI and near-far effect. But it is not possible in a mobile environment to maintain orthogonality of the codes at the receiver. A potential solution is the optimum multiuser detector that consists of a bank of matched filters fol-

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lowed by a Viterbi maximum likelihood (ML) detector [1]. However the computational complexity of this detector increases exponentially with the number of users, and the method is extremely complex to implement for a realistic number of users. Therefore, there has been considerable research into suboptimal detectors. Two types of linear detectors have also been suggested. These are a decorrelating detector [2] and a minimum mean squared error (MMSE) detector [3]. The complexity of these receivers is linear with the number of users.

In non-linear multiuser detection, which is also called subtractive detection, the interference estimates are generated and then removed from the received signal before the detection. Neural network approach is one of the common interests in the non-linear detector category. There are some studies on multiuser detection using neural networks in the literature [4-15]. The neural network receiver was made first by Aazhang, Paris and Orsak [4]. They demonstrated by applying a complicated training method called assisted back propagation, where the number of neurons increases exponentially with the number of the nodes, the performance of multilayer perceptron is close to that of the optimum receiver. The receiver proposed in [5] uses radial basis function (RBF) neural network that becomes too complex under the multipath environment. The energy function of Hopfield neural network is identical to the likelihood function encountered in multiuser detection. Therefore, some researchers have used the Hopfield neural network (HNN) for multiuser detection [6-8], and also in [9] Hopfield network was used as adaptively. A neural network based decision feedback scheme for interference suppression was investigated in [10]. A compact neural network [11], an annealed neural network [12], a modified Kennedy-Chua neural network, which is based on the Hopfield model [13] was used for multiuser detection. Robust version of the linear decorrelating detector with three layers recurrent neural network was proposed in [14]. The performances of two-layer perceptron neural network using back propagation training algorithm as multiuser detector for CDMA signals in AWGN (additive white Gaussian noise) and fading channels were analyzed in [15]. In [15] also the performances of decision based neural network, fuzzy decision neural network and discriminative learning neural network with the back propagation net were compared in AWGN channel. Jang and et al. have proposed a fuzzy system for multi-user detection by using same simulation aspects with [4] and have obtained good BER performance [16]. There hasn’t been any study in the literature about multi user detection in CDMA with adaptive neuro-fuzzy inference system (ANFIS).

In this study, we used an adaptive neuro-fuzzy inference system for multi-user detection in CDMA. For performance evaluation, ANFIS was compared with the neural network receiver by the computer simulations.

This paper is organized as follows: In section 2, background information in regard to the CDMA system is presented. In section 3, adaptive neuro-fuzzy inference system is described briefly. In section 4, proposed receiver is introduced. In section 5, computer simulation results are given. Finally, section 6 contains conclusions.

2. SYSTEM MODEL

We consider a synchronous CDMA system with BPSK (binary phase shift keying) modulation in an AWGN channel. Data for each user as random series in form $+1, -1$ is generated and multiplied its spreading code to obtain CDMA signal. K user synchronous transmitter system model is shown in Fig. 1 CDMA signals of all users and AWGN are added in the channel. The received signal at the output of the channel is given by

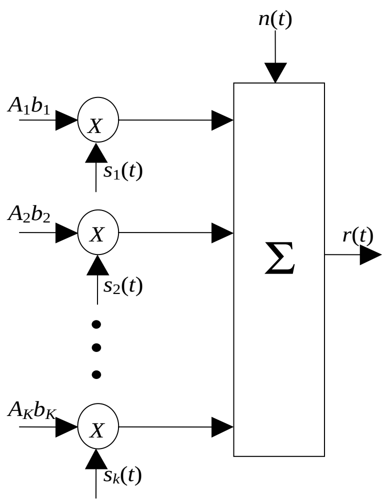

Fig. 1. K user synchronous transmitter system model.

$$r(t) = \sum_{k=1}^{K} A_k b_k s_k(t) + n(t) \tag{1}$$

where b_k is the input bit of the kth user, $b_k \in \{1, -1\}$, A_k is the received amplitude of the kth user, $n(t)$ is the additive white Gaussian noise and $s_k(t)$ is the signature waveform of the kth user. $s_k(t)$ is defined for N signature sequence length and BPSK modulation as:

$$s_k(t) = \sum_{k=0}^{N-1} a_k P_T(t - kT_c) \tag{2}$$

where T is bit period, T_c is chip interval (bit period of spreading code), P_T is the rectangular waveform of duration T_c, and $T = NT_c$, a_k is normalized spreading sequence.

The cross-correlation of the signature sequences are defined as:

$$\rho_{ij} = \langle s_i s_j \rangle = \sum_{k=1}^{N} s_i(k) s_j(k). \tag{3}$$

The cross-correlation matrix is then defined as:

$$R = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix}. \tag{4}$$

At the receiver side, received signal $r(t)$ is multiplied with kth user signature waveform and integrated in one bit period to make estimation for kth user bit. The output of the kth matched filter y_k is given by

$$y_k = \int_0^T r(t)s_k(t)dt. \tag{5}$$

Substituting Eqs. (1) and (2) in Eq. (5), the output of the matched filter for kth user is obtained like that,

$$y_k = A_k b_k + \sum_{j=1,\, j\neq k}^{K} A_j b_j \rho_{jk} + n_k \tag{6}$$

where, A_k is amplitude of the desired user, b_k is bit value of the desired user, A_j is amplitude of the jth user, b_j is bit value of jth user and ρ_{jk} is cross-correlation coefficient between desired user and jth user. In Eq. (6), first term is desired output, the others are multiple access interference (MAI) and noise. Matched filter takes the MAI as noise, for this reason its BER performance degrades as the number of active users increases.

Eq. (6) can be written in matrix form as:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_K \end{bmatrix} = \begin{bmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix} \begin{bmatrix} A_1 & 0 & \cdots & 0 \\ 0 & A_2 & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & A_K \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_K \end{bmatrix}. \tag{7}$$

Eq. (7) can be shown in matrix notation such as:

$$\boldsymbol{y} = \mathbf{Rab} + \boldsymbol{n}. \tag{8}$$

At the ANFIS receiver, estimated data is obtained with the defined rules and membership functions. The membership functions, the rules and the number of the rules are defined by training with the data that is obtained from the outputs of the matched filters. A clustering technique is used during the training. At the fuzzy receiver 2^K rules are defined for K users, but the number of the rules is much lower than this quantity at the ANFIS.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The ANFIS constructs a fuzzy inference system whose membership function parameters are tuned using the given input/output data set by using a back propagation algorithm or the hybrid learning algorithm. The network-type structure of the ANFIS is similar to a neural network. It maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs. The clustering is used to identify natural groupings of data from a large data set to produce a concise representation of a system's behavior. In our system, subtractive clustering was used, which is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. The cluster information can be used to generate a Sugeno-type fuzzy inference system that best models the data behavior using a minimum number of rules [17]. Fig. 2 illustrates how the ANFIS represents the first-order Sugeno fuzzy model. In Fig. 2, each circle indicates a fix node whereas each square indicates an adaptive node.

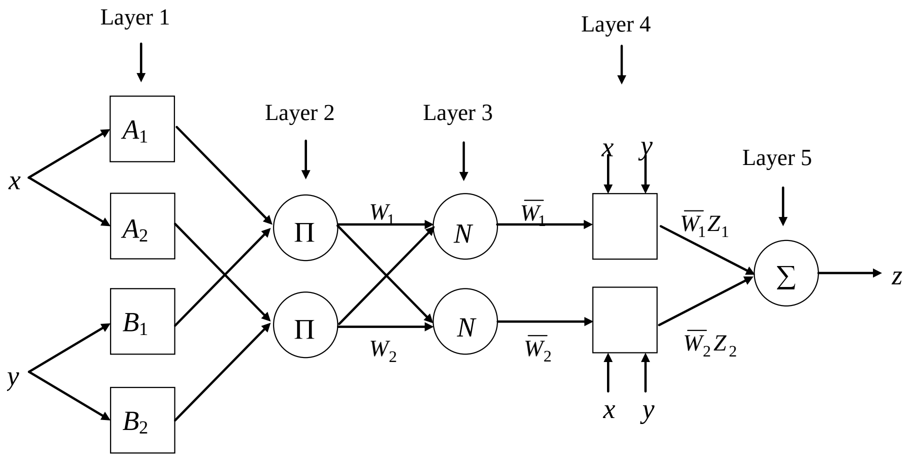

Fig. 2. Architecture of ANFIS.

For this model, a common rule set with two fuzzy if-then rules can be expressed as:

Rule 1: If x is A_1 and y is B_1, then $z_1 = p_1x + q_1y + r_1$ (9a)
Rule 2: If x is A_2 and y is B_2, then $z_2 = p_2x + q_2y + r_2$ (9b)

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the consequent parameters that are determined during the training process. As it is seen in Fig. 2, the ANFIS consists of five layers:

Layer 1: Every node i in the first layer has a node function $Q_{1,i}$ which represents the output of the ith node in layer 1 and is given by

$$Q_{1,i} = \begin{cases} \mu_{A_i}(x), & \text{for } i = 1,\ 2 \\ \mu_{B_{i-2}}(y), & \text{for } i = 3,\ 4 \end{cases} \tag{10}$$

where x (or y) is the input to node i, A_i (or $B_{i\text{-}2}$) is the linguistic term associated with the node, and μ_i (or $\mu_{B_{i\text{-}2}}$) is the membership function for the term A_i (or $B_{i\text{-}2}$). In other words, each node function specifies the degree to which the given input x (or y) satisfies the qualifier A_i (or $B_{i\text{-}2}$).

Layer 2: Each node output represents the firing strength of a rule and performs the fuzzy

AND operation. The output of the node i is the product of all the incoming signals for the ith rule and is given by

$$Q_{2,i} = \omega_i = \mu_{A_i}(x)\mu_{B_i}(y), \text{ for } i = 1, 2. \tag{11}$$

Layer 3: The ith node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths. The output of node i in this layer is the normalized firing strength that is given by

$$Q_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2}, \; i = 1, \; 2. \tag{12}$$

Layer 4: In this layer, every node has a node function given by

$$Q_{4,i} = \bar{\omega}_i z_i = \bar{\omega}_i (p_i x + q_i y + r_i), \tag{13}$$

where $\bar{\omega}_i$ is a normalized firing strength from layer 3, and $\{p_i, q_i, r_i\}$ is the consequent parameter sets of node i.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which has output function given by

$$Q_5 = \sum_i \bar{\omega}_i z_i = \frac{\sum_i \omega_i z_i}{\sum_i \omega_i}. \tag{14}$$

In this paper, the hybrid learning algorithm is used, which is combines the least square method and the gradient descent method. When the values of premise parameters are fixed, the overall output of the ANFIS can be written as a linear combination of the consequent parameters. In the hybrid learning rule, each training epoch consists of a forward pass and backward pass. In the forward pass, node outputs of the layer 4 are calculated and node outputs are compared with the desired values, then consequent parameters are adjusted by the least square method. In the backward pass, the error signals propagate backward and the parameters of the membership functions are updated by gradient descent method [18].

4. RECEIVER WITH THE ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

In this study, an ANFIS is used as decision device after matched filter to get user data. This structure is shown in Fig. 3. The ANFIS structure that is used in this receiver for 5 users with 8 rules is shown in Fig. 4.

In the receiver, rules are defined according to matched filter outputs. ANFIS can be trained with outputs of matched filter for two different types of data: a lot of number of bits with noise and bits as all possible combinations of the number of users (2^K for K

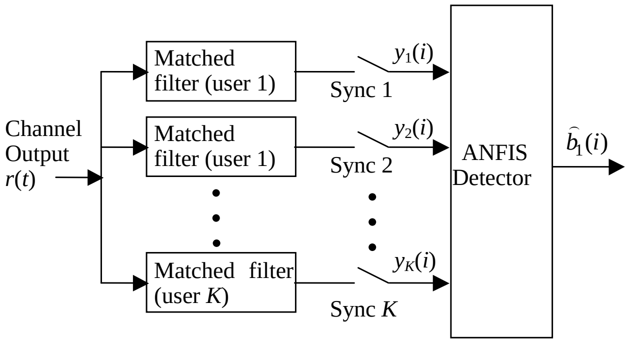

Fig. 3. Multi-user receiver structure with ANFIS for the first user.

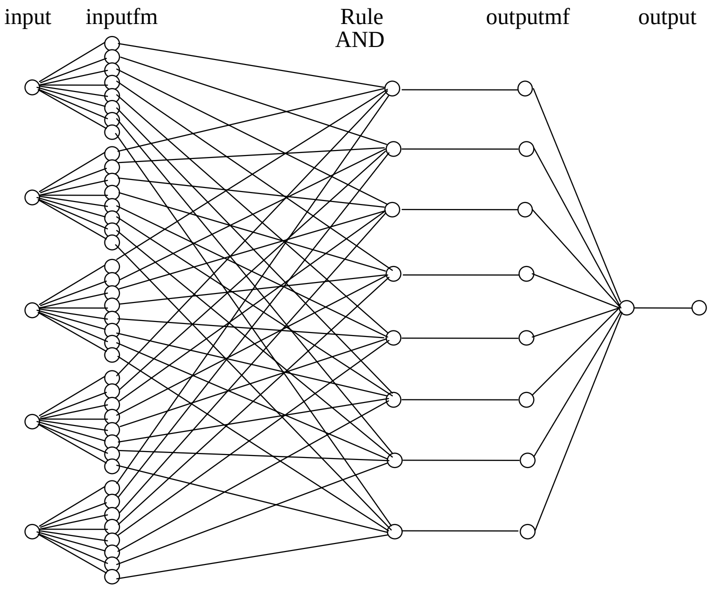

Fig. 4. ANFIS structure for 5 users with 8 rules that is used in the proposed receiver for the first user.

users) without noise. Each user output is obtained with these rules. For $k = 1, 2, \ldots, K$ and $j = 1, 2, \ldots, J$, these rules can be defined like that:

$$Rule(j)\text{: IF } y_1(j) \text{ and } y_2(j) \text{ and } y_3(j) \text{ and } \ldots\ y_K(j) \text{ THEN } output_k(j) = b_k(j)$$

where $y_k(j)$ matched filter output of kth user for jth bit, K is the number of the users, J is the number of bits, b is data of the users. However, number of the bits that is considered with this definition is lower than the number of the bits that is used in the training because of using the clustering with ANFIS.

5. SIMULATION RESULTS

Simulations have been carried out in three different ways for 31 bits length spreading codes: BER of the desired user versus the signal to noise ratio (SNR), BER of the desired user versus the near-far rate (NFR) and BER of the desired user versus the number of active users. Furthermore, BER of the desired user versus the signal to noise ratio (SNR) has been examined for 3 and 7 bits length spreading codes. In the simulations, synchronous AWGN channels are considered with 5 users for 31 bits length of spreading codes, 4 users for 7 bits length of spreading codes and 2-3 users for 3 bits length of spreading codes. Simulations have been carried out through transmitter to receiver in all of the CDMA system. 31 bits length of spreading codes that are used in the simulations have normalized cross-correlation 0.2258 between each other. Cross-correlation value is selected bigger to create a more severe near-far environment. The ANFIS and the neural network were trained with the outputs of the matched filters with noise or without noise for various simulations. The SNR of the first user and the NFR of user k are defined such as:

$$SNR_1 = \frac{singal\ power}{noise\ power} = \frac{A_1^2}{2\sigma^2}\ ; \quad NFR_k = \frac{user\ k\ power}{user\ 1\ power} = \frac{A_k^2}{A_1^2}$$

where σ^2 is the variance of the noise with the zero mean value and A_k is the amplitude of user k's signal.

In the neural network that is used for comparison purpose, number of the input nodes, hidden layer nodes and output nodes equal to the number of the users. It is a feed forward network and it is trained by Levenberg-Marquardt algorithm. In the hidden layer tangent sigmoid activation function was used and in the output layer pure linear activation function was used.

In the FIS receiver, which is used to show upper bound of the ANFIS in terms of the complexity and the BER performance, the Sugeno type FIS is used. The parameters of the membership functions of the FIS are defined according to the training data set, which are outputs of the matched filters without noise. This data set consists of all the possible combinations for K users as including 2^K sets. In the used structure, all input membership functions are Gaussian and all output membership functions are triangular type and AND operand is used for proceeding inputs. 2^K rules are defined in the FIS for K users and each user output is obtained with these rules.

In the five users synchronous AWGN channel for 31 bits length spreading codes, BER values of the first user versus SNR_1 for various multi-user receivers are shown in Fig. 5. In the simulations, the NFR values are taken as 4 for user 2, and as 1 for users 3, 4 and 5. The ANFIS and the neural network were trained with the outputs of the matched filter without noise by considering 32 bits, which are all the possible combinations of five users. The ANFIS has the advantage over the neural network in terms of the training time. The ANFIS constituted 8 rules by taking advantage of using the clustering, although it can have 32 rules maximum with the large complexity for the five users. As it is seen in Fig. 5, ANFIS receiver has much better performance than the matched filter and slightly better than the neural network. The neural network has the good BER performance because of its generalizing ability after the training. The ANFIS estimates bits

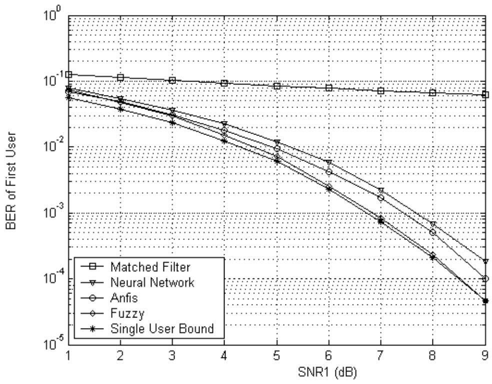

Fig. 5. BER values of the first user versus SNR_1 for various multi-user receivers. (5 users channel, NFR_2 is 4, NFR_3 = NFR_4 = NFR_5 = 1, with 31 bits length codes).

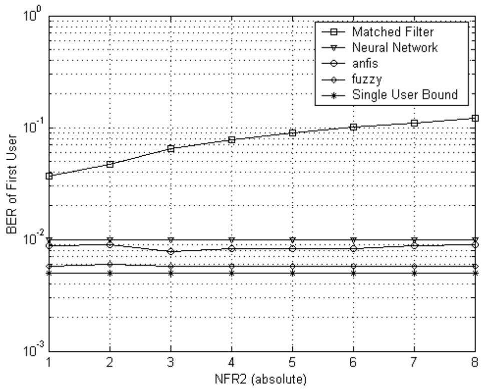

Fig. 6. BER values of the first user versus NFR_2. (5 users channel, SNR value of the first user is 5 dB, NFR_3 = NFR_4 = NFR_5 = 1, with 31 bits length codes).

better than the neural network especially for the higher SNR values because the ANFIS processes the data with the certain rules defined with the training. The BER performance of the FIS receiver is very close to the single user bound because the rule set of the FIS consists of the all the possible 32 combinations. The FIS has the much bigger processing time than the ANFIS because of its more rules. So, ANFIS receiver has a lower computational complexity than the FIS receiver and it has a better BER performance than the neural network. According to the simulation results which are shown in Fig. 5, ANFIS receiver has higher BER values than FIS receiver for SNR values that is higher than 3 dB whereas both receivers have the same BER values until 3 dB. In the ANFIS and FIS receivers that work according to defined rules, BER performance can degrade for smaller SNR values. However, it is seen that receivers that work with the rules can make better detection for bigger SNR values. Having better BER performance of FIS receiver at the higher SNR values shows that the increment in the number of the defined rules increases the accuracy of detection. However, in the neural receiver that works according to generalizing technique, BER performance is not good as well as ANFIS receiver at the bigger SNR values.

BER values of the first user versus NFR_2 are shown in Fig. 6. Channel conditions are the same with previous simulation, SNR value of the first user is 5 dB and amplitudes of other users are equal to amplitude of the first user. The ANFIS and the neural network were trained with the outputs of the matched filter without noise and NFR value at the training is assumed as 3. The ANFIS has 8 rules and the small training time. As it is seen in Fig. 6, the sensitivity of the neural network to the near-far effect is relaxed and it has a good and stable BER performance. The ANFIS is affected by the changes of amplitudes of the user signals with small amounts. Because it processes with the membership functions, which has parameters that depends on amplitude values defined during the training. For this reason, ANFIS receiver has the best performance at the value of 3 that is assumed during the training. However the BER performance of the ANFIS receiver is still better than the BER performance of the neural network. The BER performance of the FIS receiver is close to single user bound with the big complexity. However, the ANFIS receiver has lower computational complexity than the FIS receiver.

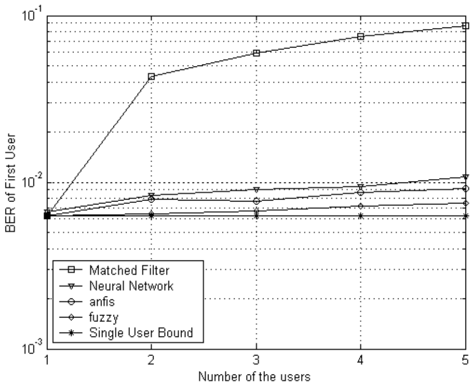

Fig. 7. BER values of the first user versus the number of the users. (SNR value of the first user is 5 dB and perfect power control is assumed, with 31 bits length codes).

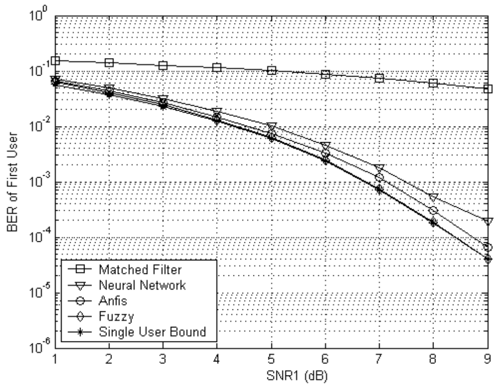

Fig. 8. BER values of the first user versus SNR_1 for various multi-user receivers. (NFR_2 is 4, 2 users channel, with 3 bits length codes).

BER values of the first user versus the number of the users are shown in Fig. 7. SNR value of the first user is 5 dB and perfect power control is assumed. The neural and ANFIS receivers were trained for 3 users. The BER performances of the all receivers in the CDMA system degrade with the number of the users. In that case, BER performance of the ANFIS receiver degrades a little bit with the number of the users, but it is still better than the neural network receiver. ANFIS receiver has the best performance for 3 users that is assumed during the training. Also in terms of the number of users, fuzzy receiver is the closest to the single user bound because of having much rules than ANFIS receiver.

The performance of the ANFIS receiver was also examined with various spreading codes, which are used in the literature. But, these examinations were done just for BER versus SNR_1 performance. BER values of the first user versus SNR_1 are shown in Fig. 8 and Fig. 9 for 3 bits length codes, which are used in [4] and [16]. These codes are (1 1 1) for first user, (1 –1 1) for second user and (1 1 –1) for third user. Simulations were done for 2 users and 3 users channels. NFR_2 is assumed 4 (absolute) and NFR_3 is assumed 1. The ANFIS and the neural network were trained by 500 bits data with noise (SNR = 10dB). Results were shown for 2 users and 3 users channels in Figs. 8 and 9, respectively. It is seen that the ANFIS has better performance than the neural network also for these codes. ANFIS has gotten 4 rules for both cases with lower complexity than the neural network and the FIS receiver. In Fig. 8, ANFIS and FIS receivers have approximately same performance until 4 dB SNR value whereas FIS receiver has lower BER values than ANFIS receiver having 8 rules after 4 dB SNR value. Moreover, BER performance of the FIS receiver also coincides with the single user bound after 4 dB SNR value. In Fig. 9, the difference in the BER performance of the FIS and the ANFIS receivers is small for small values of SNR, but as SNR values increase, the difference in BER performance of the FIS and the ANFIS receivers also increase. BER performances of all receivers are worse than the performance in Fig. 8 because of the increment in the number of the users.

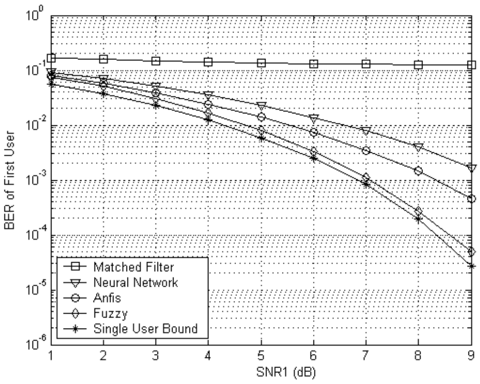

Fig. 9. BER values of the first user versus SNR_1 for various multi-user receivers. (NFR_2 is 4, NFR_3 = 1, 3 users channel, with 3 bits length codes).

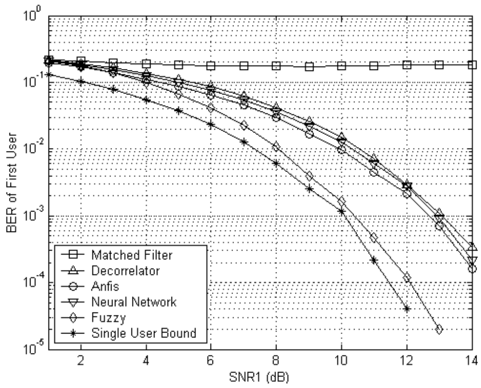

Fig. 10. BER values of the first user versus SNR_1 for various multi-user receivers. (4 users channel, $NFR_2 = NFR_3 = NFR_4 = 2$, with 7 bits length codes).

BER values of the first user versus SNR_1 are shown in Fig. 10 for 7 bits length codes, which are used in [15]. SNR_1 was assumed $(A_1)^2/\sigma^2$ for this simulation as in [15]. These codes and normalized correlation matrix are given as:

$$S = \begin{bmatrix} 1 & -1 & -1 & 1 & 1 & 1 & -1 \\ 1 & 1 & -1 & -1 & -1 & -1 & -1 \\ -1 & 1 & -1 & 1 & 1 & 1 & -1 \\ 1 & -1 & -1 & -1 & -1 & 1 & -1 \end{bmatrix}; \quad R = \begin{bmatrix} 1 & -0.14 & 0.43 & 0.43 \\ 0.14 & 1 & -0.14 & 0.43 \\ 0.43 & -0.14 & 1 & -0.14 \\ 0.43 & 0.43 & -0.14 & 1 \end{bmatrix}.$$

Simulations were done for 4 users AWGN channel with $NFR_2 = NFR_3 = NFR_4 = 2$. ANFIS and neural network were trained by 500 bits data with noise (SNR = 10dB). ANFIS has again better performance than the neural network and it has lower complexity, with 5 rules. In Fig. 10, ANFIS and FIS receivers have approximately same performance until 3 dB SNR value whereas FIS receiver has lower BER values than ANFIS receiver having 16 rules after 3 dB SNR value. BER performances of all receivers are worse than the performance in previous figures because of the increment in the number of the users, assuming of SNR_1 as $(A_1)^2/\sigma^2$ and having bigger cross-correlation of codes.

The effects of training the ANFIS were examined with two experiments. Firstly, effect of training data with noise and without noise was examined. 31 bits length spreading codes were used, $NFR_2 = 4$, $NFR_3 = NFR_4 = NFR_5 = 1$ were assumed and simulation was done for 5 users AWGN channel. The ANFIS was trained by 500 bits data with noise or 32 bits data without noise. As it is seen in Fig. 11, the ANFIS that is trained by data without noise has better performance than the other. ANFIS has gotten 4 rules by training data with noise, has gotten 8 rules by training data without noise. The smaller amounts of the clusters were constituted by using a bigger amount of the training bit with noise but in that case rules consist of the noise. Decrement in the number of the cluster causes worse defined rules and also causes insufficient number of the rules. In Fig. 11, the ANFIS receiver that is trained by data without noise has lower BER values than the

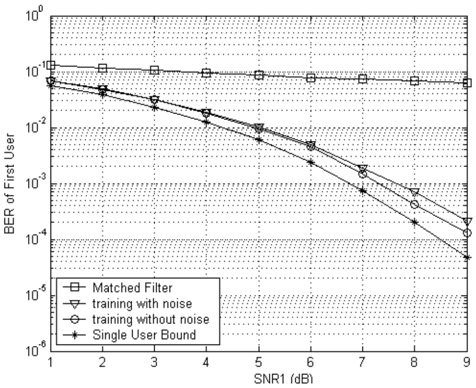

Fig. 11. BER values of the first user versus SNR_1 for comparison ANFIS receivers that are trained with noise and without noise. (5 users channel, NFR_2 is 4, $NFR_3 = NFR_4 = NFR_5 = 1$, with 31 bits length codes).

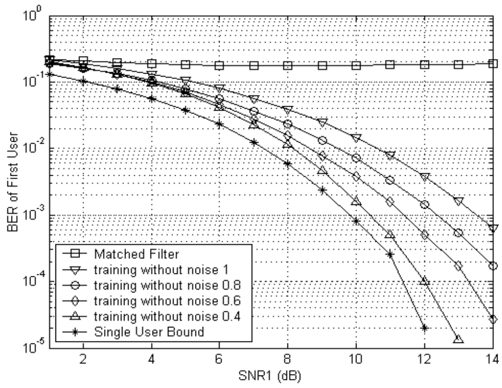

Fig. 12. BER values of the first user versus SNR_1 for comparison ANFIS receivers that are trained by data with various cluster radius without noise. (4 users channel, $NFR_2 = NFR_3 = NFR_4 = 2$, with 7 bits length codes).

ANFIS receiver that is trained by data with noise for SNR values that is higher than 4 dB whereas both receivers have the same BER values until 4 dB. So, the ANFIS that is trained by data without noise has better BER performance, but has a higher complexity. Secondly, effect of radius of cluster during the training was examined. Experiment was done with conditions that are used in Fig. 10, but training data without noise was used. Four different radius of cluster (1, 0.8, 0.6 and 0.4) were used for clustering data during the training ANFIS. Decreasing radius causes increasing of the number of the clusters and therefore causes the increasing of the number of the rules. ANFIS has gotten 8 rules for radius 1, 14 rules for radius 0.8, 16 rules for radius 0.6 and 0.4. As it is seen in Fig. 12, decreasing radius causes performance improvement. However, decreasing the cluster radius increases complexity, but also there is interesting result for radius 0.6 and 0.4, performance is different although the same rule number. Decreasing radius more than 0.6 doesn't increase number of the rules, because 16 rules maximum can be defined for 4 users. However smaller cluster radius assures more well defined rules that helps better detection though the same number of rules.

6. CONCLUSION

In this study, we investigated multi-user receiver with ANFIS. We have got better BER performances than the neural network receiver's. A fuzzy inference system (FIS) that we constituted was used to show upper limits of the ANFIS in terms of the BER performance and the complexity. In the FIS, the number of the rules increases exponentially with the number of the users. However, the number of the rules in the ANFIS is defined by clustering data and it is much lower than the number of the rules of FIS. The ANFIS receiver has 8 rules while the FIS receiver has 32 rules for 5 users. Computational complexity is the similar for ANFIS and neural network but the training time of the ANFIS is smaller than neural network's. Furthermore, it was seen that ANFIS, which is trained by data without noise and with smaller cluster radius, has a better BER performance with a higher computational complexity.

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Yalcin Isik received the B.S. degree in Electronics Engineering from Gazi University and M.S. degree in Electronics Engineering from Hacettepe University, Turkey in 1985 and 1988, respectively. He is now an instructor at Electronic Communications Program of Vocational High School at the Erciyes University of Turkey. He is now a doctorate student in Electronics Engineering of Erciyes University, Turkey. His current research interest includes multiuser detection in CDMA, neural networks, and Fuzzy systems.

Necmi Taşpınar was born in Afyon, Turkey, on January 2, 1963. He received the B.Sc. degree in Electronic Engineering from the Erciyes University, Kayseri, Turkey in 1983, the M.S. degree in Electronic and Telecommunications Engineering from the Technical University of Istanbul, Istanbul, Turkey in 1988, and the Ph.D. degree in Electronic Engineering from the Erciyes University, Kayseri, Turkey in 1991. From 1984 to 1992 he was a Research Assistant, during 1992-1996 he was an Assistant Professor, during 1996-2002 he was an Associate Professor, and since 2002 he has been Full Professor in the Department of Electronic Engineering, Engineering Faculty, Erciyes University, Kayseri, Turkey. His research interests include theory and applications of error-control coding, multiuser detection, equalization, CDMA and spread-spectrum systems, OFDM systems, routing, and applications of neural networks, genetic algorithms and fuzzy logic to communications problems.