A Fuzzy Supervised Learning Algorithm for Channel Optimization in CDMA Systems

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Summary
In this paper, a fuzzy supervised learning algorithm is proposed, which shows more improved learning time and convergence property than that of the conventional fuzzy neural network. First, we investigate the structure of physiological neurons of the nervous system and propose new neuron structure based on fuzzy logic. And by using the proposed fuzzy neuron structures, the model and learning algorithm of a new fuzzy learning are proposed. Two types of guard channels are introduced and analytic model of channel allocation is developed for soft handoff scheme in CDMA systems. To solve the optimal channel allocation, the proposed algorithm is applied. The experiment results show that the proposed method is efficient in the optimal channel allocation.

Key words:
fuzzy neural network, physiological neurons, guard channel, soft handoff, CDMA

1. Introduction

The study of brain provides insights at many different levels of analysis from cognitive behaviors such as problem solving, language production, etc. to molecular structure of a neuron. Our approach is concerned to human neural mechanism in two aspects based on levels of analysis. One is the symbolic processing that programs the knowledge in the brain and can be considered the analysis of functional level. The other is to implement the knowledge at the level of artificial neural structure. These two methods are melting into a hybrid fuzzy neural network.

We analysis the exciting neuron in the physiological structure and classify an inhibited neuron into a forward inhibitory neuron and a backward inhibitory neuron. And fuzzy logic has a merit of induction, and is composed of fuzzy set theory and fuzzy logic operation. There are fuzzy AND, fuzzy OR, and fuzzy NEGATION in the conventional fuzzy logic operations [1][2]. The conventional perceptron, due to its use of unit step function was, highly sensitive to change in the weights, difficult to implement and could not learn from past data [3][4]. In this paper, we propose a fuzzy supervised learning algorithm, a modification to the conventional fuzzy perceptron that replace the generalized delta rule using a physiological neuron structure. Therefore, we define a proposition that a forward inhibitory neuron is fuzzy logical-AND organization and a backward inhibitory neuron is fuzzy logical-NEGTION organization. We define a fuzzy OR structure by analyzing excitatory neuron in the physiological neuron organization. The fuzzy learning algorithms that combine the merits of fuzzy logic with the neural networks based on physiological organization are proposed in this paper. We applied the proposed algorithm to the optimal channel allocation problem in CDMA (code division multiple access) systems. The optimal channel allocation problem is closely related to the phenomenon called handoff.

In a CDMA system, the geographic region covered by the system is divided into small region called cell. Each cell denotes the region covered by a particular base station (BS), which acts as a relay of the signals it receives. Due to their cellular structure, when a mobile station (MS) moves one cell to another, the channel allocated to the mobile station must be released and a new channel from the destination cell must be obtained. This process is called handoff and associated call is called a handoff call. Handoff calls are more important than new calls since forced termination is more uncomfortable than blocking a new call. So, to reduce the blocking probability of handoff calls, a fixed number of channels are reserved exclusively for the handoff calls [6]. These channels are called guard channels.

Considering the optimal channel allocation problem, the optimality is achieved by minimizing the GoS (Grade of Service) in the sense of call blocking rate. GoS is defined by the following equation [7]:

$$GoS = P_b + \omega P_d \tag{1}$$

Where P_b is the probability of its blocking a new call, P_d is the probability of blocking a handoff call (dropping probability) and ω is a weighting factor that decides how much emphasis is placed on handoff calls.

By using the guard channel policy, dropping probability can significantly be reduced. However, reserving guard channels could result in blocking probability increase. In

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fact, as shown in [8], for fixed N, P_d is a decreasing function of g and P_b is an increasing function of g. Therefore, to minimize the GoS, an optimal guard channel number g should be computed. In a CDMA system, a cell can be partitioned into two regions: normal region (NR) and the soft handoff region (SHR). Each cell intersects with its neighbor cells. The intersection region of two cells is considered the SHR. In the SHR, a mobile station can be serviced by any of the cells that make up the intersection. Therefore, to optimize the GoS, two types of guard channel numbers are required. One, g_n, is guard channel number for NR and the other, g_h, is that for SHR. In this paper, we compute the optimal guard channel number g_n and g_h using the proposed fuzzy supervised learning algorithm. The remaining part of the paper is organized as follows. Section 2 describes the system architecture for channel optimization. Section 3 proposes a fuzzy supervised learning algorithm. Section 4 covers the definition of the optimal channel allocation problem in CDMA systems. We show experimental results in section 5, and the paper concludes in Section 6.

2. System Architecture for Channel Optimization

The system architecture for channel optimization is shown in Fig. 1. It consists of two major modules: FTSM (Fuzzy Training Structure Module) and CAM (Channel Allocation Module). The FTSM has two sub modules named Classifier and Generator. The Generator makes the rules and the membership degrees from the training data and then, the Classifier classifies the optimal guard channel values using the rules made by the Generator. The main function of the CAM is allocating the channels and is computing the GoS for the optimal guard channel numbers under given traffic load environment

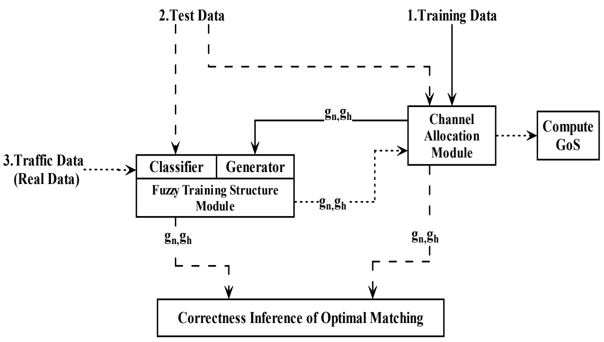

Fig. 1. System architecture

The proposed channel optimization procedure is as follows:

- Step 1 (developing a fuzzy supervised learning model): The details will be described in section 3.
- Step 2 (developing the channel allocation model for CDMA system): In section 4, we will describe the details.
- Step 3 (implanting the decision rules into the fuzzy supervised learning module): We will implant the rules for deciding the number of guard channel into the proposed fuzzy supervised learning algorithm. For this, we make some sample data using the CAM of Step 2. Each datum is a tuple of given traffic parameters: N, λ_n, α, g_n, g_h. CAM computes the optimal guard channel numbers: g_n, g_h for given traffic. The guard channel numbers are trained by using the proposed fuzzy supervised learning algorithm. The solid line in Fig. 1 depicts the process. In this Step, we classify the training data of the guard channel numbers.
- Step 4 (analyzing the fuzzy supervised learning algorithm): To show the correctness of the implanted rules, compare the result of the fuzzy supervised learning algorithm with the solution of the CAM for unlearned combinations of N, λ_n, α. The dashed line in Fig. 1 depicts this process.
- Step 5 (applying the system for real data): Finally, applying the system for real data, we evaluate the performance of the system. The dotted line in Fig. 1 depicts the process.

3. A Fuzzy Supervised Learning Algorithm

3.1 A Fuzzy Supervised Learning Model

We defined a fuzzy OR structure by analyzing excitatory neuron in the physiological neuron organization. We also defined a fuzzy AND structure by classifying the inhibitory neuron structure as the forward inhibitory neuron structure and the backward inhibitory neuron structure. The interneuron is defined as fuzzy NEGATION. The proposed learning structure is shown in Fig. 2.

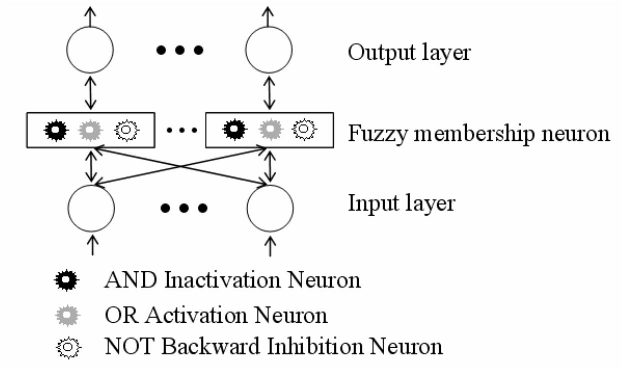

Fig. 2. A Fuzzy Supervised Learning Model

3.2 A Fuzzy Supervised Learning Algorithm

The learning steps are classified as the forward step and the backward step in the proposed fuzzy supervised learning algorithm. In the forward steps, the actual output values are calculated through the fuzzy neuron membership function. The initial weight range is established by [4][5].

We use fuzzy logic operator Max & Min instead of sigmoid function. With these operators, Max operator can be used if target value is '1' or Min operator if '0'. In the backward steps, the weight is adjusted by dividing each neuron into excitatory neuron and inhibitory neuron in accordance with the fuzzy neuron membership function. The proposed algorithm as follows:

Step 1: Initialize Logic_value, Logic_weight, and Logic_mark

Logic_weight : $W_{AND_{ji}} = 1, W_{OR_{ji}} = 1, W_{NT_{ji}} = 1$

Logic_value : $V_{AND_{ji}} = 1/I, V_{OR_{ji}} = 1, V_{NT_{ji}} = -1$

Logic_mark : $ON_{AND^p_{ji}} = 1, ON_{OR^p_{ji}} = 1, ON_{NT^p_{ji}} = 1$

where, $W_{AND_{ji}}$: forward inhibitory operation

$W_{OR_{ji}}$: forward inhibitory operation,

$W_{NT_{ji}}$: backward inhibitory operation

Step 2: Read input pattern

Step 3: Select target bit j for input pattern

Step 4: Calculate and normalize Synapse_value from 0 to 1

$$Synapse_{ji} = Synapse_{ji} + \left(ON_{AND^p_{ji}} \times x^p_i \times V_{AND_{ji}} \times W_{AND_{ji}}\right) + \left(ON_{OR^p_{ji}} \times x^p_i \times V_{OR_{ji}} \times W_{OR_{ji}}\right)$$

$$if\ \left(Synapse_{ji} > 1.0\right) then\ Synapse_{ji} = Synapse_{ji} + V_{NT_{ji}}$$

Step 5: Determine Soma_value for output value

$$if\ \left(t\arg et^p_j = 1.0\right)\ then\ Soma_j = \vee\left(Synapse_{ji}\right)$$

$$if\ \left(t\arg et^p_j = 0.0\right) then\ Soma_j = \wedge\left(Synapse_{ji}\right)$$

$$where,\ 1 \le p \le P,\ P: Number\ of\ pattern$$

$\vee$: Fuzzy MAX operation, $\wedge$: Fuzzy MIN operation

Step 6 : Update Logic_weight and Logic_mark value

$$if\ \left(\left(W_{AND_{ji}} \le 1.0\right) and\ \left(ON_{AND^p_{ji}} = 1\right)\right) then$$

$$W_{AND_{ji}} = W_{AND_{ji}} + \beta \times error_j \times \left(\left(x^p_i \times W_{AND_{ji}}\right) / insize\right)$$

$$ON_{AND^p_{ji}} = 1$$

$$if\ \left(W_{AND_{ji}} > 1.0\right)\ then\ W_{AND_{ji}} = W_{AND_{ji}} - 1.0,\ ON_{AND^p_{ji}} = 0$$

$$if\ \left(\left(W_{OR_{ji}} \le 1.0\right) and\ \left(ON_{OR^p_{ji}} = 1\right)\right) then$$

$$W_{OR_{ji}} = W_{OR_{ji}} + \beta \times error_j \times \left(x^p_i / insize\right),\ ON_{OR^p_{ji}} = 1$$

$$if\ \left(W_{OR_{ji}} > 1.0\right)\ then\ W_{OR_{ji}} = W_{OR_{ji}} - 1.0,\ ON_{OR^p_{ji}} = 1$$

$$where\ \beta: Learning\ rate,\ insize: Gravity\ Center$$

Step 7 : Repeat step 3, until it process all target bits

Step 8 : Repeat step 2, until it process all input patterns

4. Optimal Channel Allocation

4.1 Soft Handoff in CDMA Cellular Systems

In CDMA cellular systems, each cell intersects with its neighbor cells. The intersection area of two cells is considered the handoff region. In the handoff region, a CDMA mobile can be serviced by any of the cell that make up the intersection and communicates with two or more base stations until the communication link between the mobile and one base station is firmly established. This mechanism is called soft handoff. Because the soft handoff is exist, when we considering the performance model of a single cell in a CDMA cellular system, the cell can be divided into two regions, NR and SHR [8], as shown in Fig. 3.

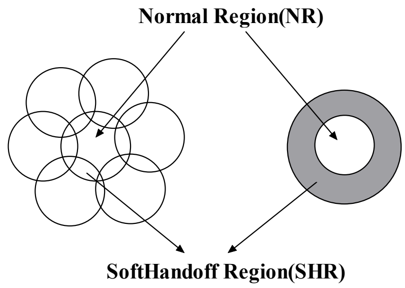

Fig. 3. Cellular System Model of Soft Handoff

4.2 Analytic model

There are three kinds of calls entering a cell: new calls in both NR and SHR, and handoff calls. Those call arrivals in a cell are assumed to be Poissonian with rates λ_{n1}, λ_{n2}, and λ_h, respectively. An ongoing call (new or handoff) completes service at the rate μ_t and the mobile engaged in the call departs the cell at the rate μ_d There is a limited number of channels N, in the channel pool.

In this paper, two different guard channels, g_n for NR and g_h for SHR, are introduced. We assume that $g_n < N$ and $g_h < N$ in order not to exclude new call altogether. When a new call arrives at the NR (SHR), it is accepted if there are more than g_n (g_h) idle channels available; otherwise, the new call is blocked. The handoff call is placed into a queue waiting for a free channel when there are no idle channels available. The call will be dropped either if the queue is full or if time out occurs**.** The maximum handoff queue length is le .

System state is defined as a row vector s such that $s = (i, j, k)$ if the number of busy channels in NR $= i$ and those channels in SHR $= j$, and the number of mobiles in the handoff queue $= k$ The state space of all feasible states is defined by

$$S = \{s = (i, j, k) \mid 0 \le i + j \le N, 0 \le k \le le\} .$$

Within the state space S, the following six kinds of events that make state transitions are possible:

- Admitting a new call in NR with rate λ_{n1} and in SHR with rate λ_{n2} .
- The normal termination of a call while a mobile is in the NR with rate μ_t .
- Ongoing calls leaving from the cell: a mobile can move to adjacent cell (handoff out), or make normal termination in the SHR with rate μ_d .
- Handoff calls arrival and departure: A mobile can moves from NR to SHR with rate m_1 or from SHR to NR with rate m_2 while talking.
- Admitting a handoff call in SHR with rate λ_h when the cell is not overloaded. Handoff calls entering into the queue: If the effective load is over the threshold, the soft handoff call can wait in the queue. While waiting in the queue, a call will be dropped if a time out event, with rate μ_o , occurs. The effective load is calculated through $N_1 + \alpha N_2$, where N_1 (N_2) is number of calls in the NR (SHR); α is the weight.

Fig. 4 illustrates a simple example of the state transition diagram with the state space of S , where N=4, g_n =2, g_h =1, le =1. For state *(i,j,k)*, the transition rates are shown in (2)-(5).

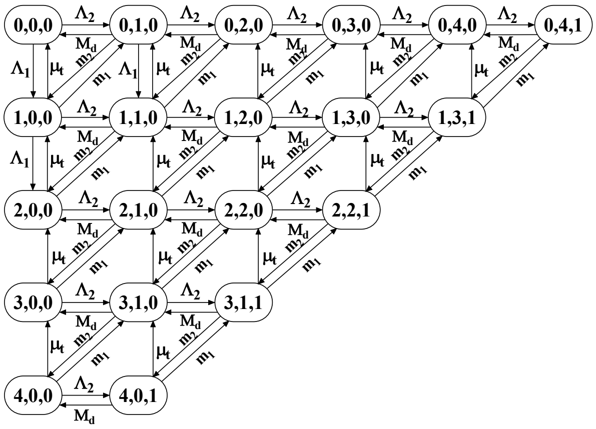

Fig. 4. Cellular System Model of Soft Handoff

Since a new call in a NR (SHR) will be blocked if the number of busy channels is greater than N- g_n (N- g_h), the equation (2) and (3) are obtained. When there are no available channels, handoff calls can wait in the handoff queue. In this case, the handoff calls in the queue would not get channels from the target cell until the calls move out of the radio coverage of the neighboring cell and are dropped.

$$\Lambda_1 = \begin{cases} \lambda_{n1} & \text{if } 0 \le i + j < N - g_n, k = 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\Lambda_2 = \begin{cases} \lambda_{n2} + \lambda_h & \text{if } 0 \le i + j < N - g_h, k = 0 \\ \lambda_h & \text{if } N - g_h \le i + j \le N, k = 0 \\ \lambda_h & \text{if } i + j = N, 0 < k < le \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

$$\mathrm{M}_d = \begin{cases} \mu_d & \text{if } 0 \le i + j < N - g_h, k = 0 \\ \mu_t + \mu_d & \text{if } N - g_h \le i + j < N, k = 0 \\ \mu_t + \mu_d + \mu_o & \text{if } i + j = N, 0 < k \le le \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

Let $P_{i,j,k}$ be the steady-state probability of state *(i,j,k).* Then, the flow balance equation of the system is given by

$$\begin{aligned} & \Lambda_1 P^*_{i-1,j,k} + \Lambda_2 P^*_{i,j-1,k} + \mu_t P^*_{i+1,j,k} \\ & + \mathrm{M}_d P^*_{i,j+1,k} + m_1 P^*_{i+1,j-1,k} + m_1 P^*_{i-1,j+1,k} \\ & = (\Lambda_1 + \Lambda_2 + \mu_t + \mathrm{M}_d + m_1 + m_2) P_{i,j,k} \end{aligned} \quad (5)$$

In (5), $P^*_{i,j,k}$ is the binary indicator variable whose value is $P_{i,j,k}$ if $(i, j, k) \in S$, and otherwise, zero. The steady-state probability $P_{i,j,k}$ is obtained by equation (5) and the following normalization condition

$$\sum_{(i,j,k)\in S} P_{i,j,k} = 1 \quad (6)$$

4.3 Optimization for Guard Channel

We consider the problem of finding the optimal number g_n and g_h such that GoS is minimized. In the sense that GoS is a linear combination of P_b and P_d , and P_b and P_d are functions of g_n and g_h . And above all, as shown in Fig. 5, the guard channel classification makes some improvement in the GoS measure. Therefore, we should find the optimal value for g_n and g_h to minimize the GoS . In order to solve the optimization problem, the proposed learning algorithm is used.
With different new call arrival rates, the corresponding handoff call arrival rates vary accordingly. To capture this dynamic behavior, a fixed point iteration scheme is applied to determine the handoff arrival rates [9][10]. To specify and solve the channel allocation model, the tool SPNP [11] is used.
A new call may arrive in ether NR or SHR. The ratio a of the SHR to the entire cell region is defined as

$$a = \frac{\text{the area of NR}}{\text{the area of the cell}} .$$

Assume that new calls are uniformly distributed in the cell, the new call arrival rates for the two regions are λ_{n1} = $a * \lambda_n$ and λ_{n2} = $(1-a) * \lambda_n$. We have assumed $a = 0.7$, μ_t =0.5(2/min), μ_d =0.65(1.5/min), μ_o =4(0.25/min), le =1, m_1 =0.5, m_2 =0.1.
In Fig. 5, we have plotted the GoS as function of the number of guard channels, g_n , in NR for different values of g_h in SHR. We get the optimal value of g_n and g_h as 3 and 2, respectively with given traffic parameters N=10, α =0.8, λ_n =4.

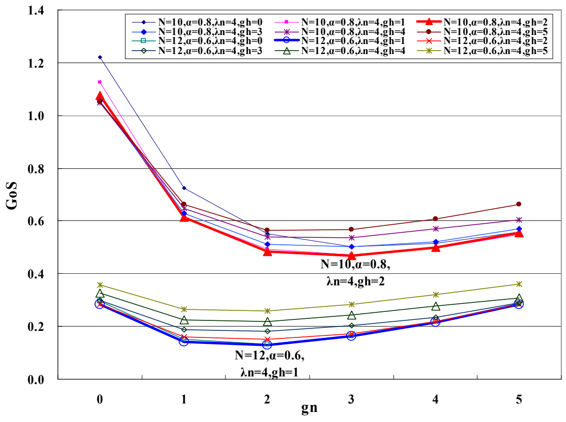

Fig. 5. GoS versus guard channel numbers

5. Experimental Results

We have implemented our learning algorithm in Visual C++ 6.0 on an Intel Pentium-IV machine with 2 GHz CPU and 512 MB of RAM. In order to analyze the learning performance of our learning algorithm, we chose the classification problem for 145's the optimal guard channel numbers. We fixed error criteria value to 0.07. We set initial learning rate at 0.5 in our algorithm. In our proposed algorithm, we set up the range of initial weight at [0, 1] by [5].
Table 1 is the summary of learning results measured in terms of Epoch and TSS (Total Sum of Square). In our proposed algorithm, the network was converged on the optimal channel allocation problem in CDMA systems. Fig. 6 shows the curve that is the sum of the square of errors in the proposed method.
As shown in Fig. 6, the proposed method has faster speed of primary convergence. And, it is known that the proposed algorithm guarantees the convergence.

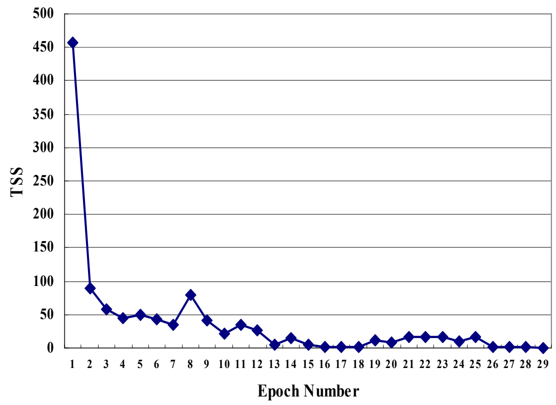

Fig. 6. Variance of TSS according to the proposed learning method

Table 1. Training results of the guard channel numbers

	A Fuzzy Supervised Learning Algorithm
Epoch Number	29
TSS	0.677930

Table 2 shows the classified results from the proposed learning algorithm for guard channel numbers. As shown in Table 2, all 147's the optimal guard channel numbers were successfully trained from the proposed algorithm and were the accuracy rate of classification is 98% in this study.

Table 2. Error rate of the optimal guard channel classification

# of guard channel	*Error rate of the proposed algorithm*
145	0.013457

6 Conclusions

The study and application of fusion fuzzy theory with logic and inference and neural network with learning ability have been actually achieving according to expansion of automatic system and information processing, etc.

We proposed a physiological fuzzy learning algorithm on the theoretical basis of fuzzy logic and physiological neural network. The proposed network is able to extend the arbitrary layers and has high convergence in case of two layers or more. When we considered only the case of the single layer, the networks had the capability of the high speed learning process and the rapid processing on huge patterns. The proposed fuzzy learning algorithm is the learning method, which contains logic operations to imitate the structure of human brains. This algorithm combines the learning ability, which is the merit of artificial neural network, with the manipulation of human's obscure expression, which is the merit of fuzzy logic.

We applied the proposed fuzzy supervised learning algorithm to optimal guard channel problem in CDMA systems and the result shows the possibility of the application to the optimal channel allocation in CDMA systems. An additional contribution of this paper is a refined analytic model of channel allocation for soft handoff scheme in CDMA systems.

In the future study, we will investigate and develop the optimal classification for the optimal channel allocation.

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