Fuzzy Hopfield Neural Network Approach to the Channel Assignment Problem

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Abstract-This paper presents a novel approach to solve channel assignment problems by using clustering technique with Fuzzy Hopfield neural network (FHNN). Channels are regarded as data sample and cells are taken as clusters. Channels are adequately distributed to the dedicated cells while satisfying the interference constraints. The goal is to avoid the interference and serve the expected traffic with minimizing used spectrum. The FHNN reduces the parameter processing time and increases the converge rate for channels assignment problem. Simulation results depict that the FHNN provides an alternative approach of solving this category of channels assignment problems.

Keywords: Channel assignment, Clustering, Fuzzy c-means, Cellular networks.

1. Introduction

Channel assignment problems (CAP) are very important to improve traffic performance characteristics in mobile communication systems. However, the usable range of the frequency spectrum is very limited. It is an NP-complete optimization problem occurring during design of cellular radio system. In selecting a channels assignment scheme [1], the objective is to achieve a high degree of utilization. Channels are assigned to different neighboring cells to reduce interference and to increase overall system capacity [2].

Many researchers have investigated neural networks to solve the CAP. In 1991, Kunz [3] first applied the Hopfield neural network model to solve the CAP in the cellular radio network. Funabiki and Takefuji [4] proposed a neural network model composed of the hysteresis McCulloch–Pitts neurons and four heuristics were used to improve the convergence rate of channels assignment. Kim *et al.* [5] proposed a modified discrete Hopfield neural network algorithm to escape local minima. Smith and Palaniswami [6] proposed two different neural networks for solving the CAP. The first is an improved Hopfield neural network and self-organizing neural network. He *et al.* [7] proposed multistage self-organizing channels assignment algorithm with a transiently chaotic neural network. Unfortunately, with these methods, to choice optimum parameters always consumes long computation time.

In this paper, Fuzzy Hopfield neural network (FHNN) clustering technique is proposed to solve channel assignment problem. FHNN is a numerical procedure to minimize energy function to find membership grade. Therefore, the CAP is considered as the problem of solving minimizing energy function problem. Channels are adequately distributed to the cells while satisfying the interference constraints. The proposed FHNN can reduce parameter processing time and increase the converge rate for channel assignment problem.

The rest of this paper is organized as follows. Section 2 describes the fuzzy Hopfield neural network (FHNN), Section 3 describes the FHNN algorithms applied to the channels assignment problem and derived the energy function. Section 4 is given the simulation results. Finally, simple conclusions are given in section 5.

2. Fuzzy Hopfield Neural Network

The Fuzzy c-means (FCM) clustering is based on the "sum of intra-cluster distances" criterion in which each data point belongs to a cluster for fitting a degree specified by membership grades [8]. Let $Z = \{z_1, z_2, ..., z_n\}$ be a given finite unclassified data set, where z_x, x=1,2,…,n, represents a p-dimensional training sample. A fuzzy c-partition of Z is denoted by $P = \{A_1, A_2, ..., A_c\}$, where c is a predetermined number of clusters. The membership grade μ_{xi} indicates the degree of possibility that z_x belongs to i-th fuzzy cluster. The membership grade is a value between zero and one which satisfies $\sum_{i=1}^{c} \mu_{xi} = 1$, for $x = 1,2,3,...,n$ and $0 < \sum_{x=1}^{n} \mu_{xi} < n$, for $i = 1,2,3,...,c$. The cluster center v_i of fuzzy partition A_i calculated as:

$$v_i = \frac{\sum_{x=1}^{n} [\mu_{xi}]^m z_x}{\sum_{x=1}^{n} [\mu_{xi}]^m}, \text{ for } i = 1,2,3,...,c \tag{1}$$

Where m is identified as the fuzzification parameter and v_i is actually the weighted mean of these samples in cluster A_i. Fuzzy clustering is to find a fuzzy c-partition and the associated cluster centers. FCM uses following procedure to update membership grade:

$$\mu_{xi} = \sum_{j=1}^{c} \left(\frac{\|z_x - v_i\|}{\|z_x - v_j\|} \right)^{\frac{-2}{m-1}} \tag{2}$$

Consider a 2-D Hopfield neural network (HNN), consisting of $n \times c$ fully interconnected neurons, for the classification problem. Let V_{xi} represents the binary states of neuron (x,i) and W_{xiyj} is the synaptic weight between neuron (x,i) and neuron (y,j). The net value of neuron (x,i) is expressed as:

$$Net_{xi} = \sum_{y=1}^{n} \sum_{j=1}^{c} W_{xiyi} V_{yj} + I_{xi} \tag{3}$$

and network total energy function is given by

$$E = -\frac{1}{2} \sum_{x=1}^{n} \sum_{y=1}^{n} \sum_{i=1}^{c} \sum_{j=1}^{c} V_{xi} W_{xiyj} V_{yj} - \sum_{x=1}^{n} \sum_{i=1}^{c} I_{xi} V_{xi} \tag{4}$$

Where I_{xi} is a bias. The rows and the columns of the Hopfield neural network represent classes and samples, respectively. The active neuron $(V_{xi} = 1)$ indicates that the sample z_x belongs to class i. Within-class scatter matrix criteria is applied in fuzzy Hopfield neural network (FHNN), and the optimization problem can be mapped into Hopfield neural network with the fuzzy c-means strategy. The total weight input for neuron (x,i) and the Lyapunov energy function can be modified [9] as:

$$Net_{x,i} = [z_x - \sum_{y=1}^{n} W_{xiyj} (\mu_{yi})^m]^2 + I_{xi} \tag{5}$$

$$E = \frac{1}{2} \sum_{x=1}^{n} \sum_{i=1}^{c} (\mu_{xi})^m [z_x - \sum_{y=1}^{n} W_{xiiyi} (\mu_{yi})^m]^2 - \sum_{x=1}^{n} \sum_{i=1}^{c} I_{xi} (\mu_{xi})^m \tag{6}$$

where $\sum_{y=1}^{n} W_{xiiyi} (\mu_{yi})^m$ is the total weight input received from the neuron (y,i), and m is the fuzzification parameter. The membership value μ_{xi} is the output state of neuron (x,i).

3. Apply to channels assignment problem

In order to apply FHNN to CAP, we have to formulate CAP as a discrete optimization problem. Suppose that there are n cells and c channels available in the network. We define a set of binary variables V_{ij}, if channel j is assigned to cell i then $V_{ij} = 1$, otherwise $V_{ij} = 0$. The cell and channel are corresponding to the cluster and the classified sample, respectively. Let $Z = \{z_1, z_2, ..., z_n\}$ be a set of channels to be assigned. The fuzzy state, i.e. a degree that a channel z_x is assigned to cell i, is denoted by μ_{xi}. After analysis the traffic data, required channels for each base station j is assumed as $traf_j$. From the constraint, we define the Lyapunov energy function as follow:

$$\begin{aligned} E = {} & \frac{A}{2} [\sum_{x=1}^{n} (\sum_{i=1}^{c} \mu_{xi} - 1)^2] + \frac{B}{2} [(\sum_{x=1}^{n} \sum_{i=1}^{c} \mu_{xi}) - d_i]^2 \\ & + \frac{C}{2} \sum_{x=1}^{n} \sum_{i=1}^{c} (\mu_{xi})^m [traf(x) - \sum_{y=1}^{n} \frac{traf(y)}{\sum_{k=1}^{n} (\mu_{ki})^m} (\mu_{yi})^m]^2 \end{aligned} \tag{7}$$

Where the element d_i represents the number of channels to be assigned to cell i; A, B, and C refer to weighting factors and are assumed to be some positive constants in our study. The first two terms of (7) are the penalty terms imposing constraints in the objective functions. The last term minimizes the within-class Euclidean distance from a sample to the cluster center.

To ensure that these n channels can be classified into c cells, the FHNN enables the scatter energy function to converge rapidly into a minimum value. Equation (7) can be simplified as [9]

$$E = \frac{1}{2}\sum_{x=1}^{n}\sum_{i=1}^{c}(\mu_{xi})^m[traf(x) - \sum_{y=1}^{n}\frac{traf(y)}{\sum_{k=1}^{n}(\mu_{ki})^m}(\mu_{yi})^m]^2 \tag{8}$$

Compare equation (8) with (5) the input to neuron (x,i) can be expressed as

$$Net_{xi} = [traf(x) - \sum_{y=1}^{n}\frac{traf(y)}{\sum_{k=1}^{n}(\mu_{ki})^m}(\mu_{yi})^m]^2 \tag{9}$$

The FHNN can classify c classes in a parallel manner and the classification algorithm is described as following steps.

Step1: Determine the number of cluster c, fuzzification parameter m, and randomly initialize the membership matrix states for all neurons.

Step2: Compute initial membership values.

$$\mu_{xi} = \sum_{j=1}^{c}\left(\frac{\|z_x - v_i\|}{\|z_x - v_j\|}\right)^{\frac{-2}{m-1}}, x = 1,2...,n; i = 1,2...,c$$

Step3: Update new membership values.

$$\mu_{xi} = \sum_{j=1}^{c}\left(\frac{Net_{xi}}{Net_{xj}}\right)^{\frac{-1}{m-1}}$$

Step4: Compute new cluster centroids.

$$v_i = \sum_{y=1}^{n}\frac{traf(y)}{\sum_{k=1}^{n}(\mu_{ki})^m}(\mu_{yi})^m \quad , \text{for } i = 1,2,3,...,c$$

Step5: Compute energy function using equation (8).

Step6: If $\left|E^{K+1} - E^{K}\right| > \varepsilon$, go to step3, otherwise stop the process.

4. The simulation results

To verify the effectiveness of our approach, the Kunz test problems described in [3] are used to simulation and compare with the results from the paper. The parameters setting in this experiment are m=2. Our problem formulation assumes that the total number of available channels is given. This number can be determined by the available radio spectrum. Table I shows the simulation results for considering the four KUNZ case. Table I shows the simulation results for considering the first 10 clusters (KUNZ1), the first 15 clusters (KUNZ2), the first 20 clusters (KUNZ3), and the first 25 clusters (KUNZ4), respectively. In the table, the running time, in terms of average and minimize for both HCNN (neural network with hill climbing) [6] and proposed FHNN algorithm are also shown for comparison the performance. The value "Min" represents the minimum energy function found, defined in (7), while "Av." is the average objective value. It is shown that the proposed FHNN algorithm is better than HCNN. Fig.1. the simulated time evolution of energy function of FHNN for KUNZ4 problem. The curve shows that the energy functions converge to a stable state after about 120 iterations. After about 120 iterations, when becomes so small that the convergent characteristic dominates the dynamics, the FHNN state finally converges to a fixed point □E=2.6□corresponding to a best local minimum.

5. Conclusions and discussion

The FHNN have been proposed for channels assignment problems, which contains interference constraints. Each frequency is regarded as a data sample and every cell is taken as a cluster. Channels are adequately distributed to the dedicated cells while satisfying the interference constraints. The FHNN reduces the parameter processing time and increase the converge rate for channels assignment problem. Simulation results depict that the FHNN provides an alternative approach of solving this class of channels assignment problems.

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Problems	cell	frequency	HCNN		FHNN	
			Av	Min	Av	Min
KUNZ1	10	30	21.1	20	17.4	17
KUNZ2	15	44	31.5	30	27.8	25
KUNZ3	20	60	13.0	13	10.6	9
KUNZ4	25	73	0.1	0	0.0	0

Table I. Computation time for HCNN and FHNN algorithm (seconds)

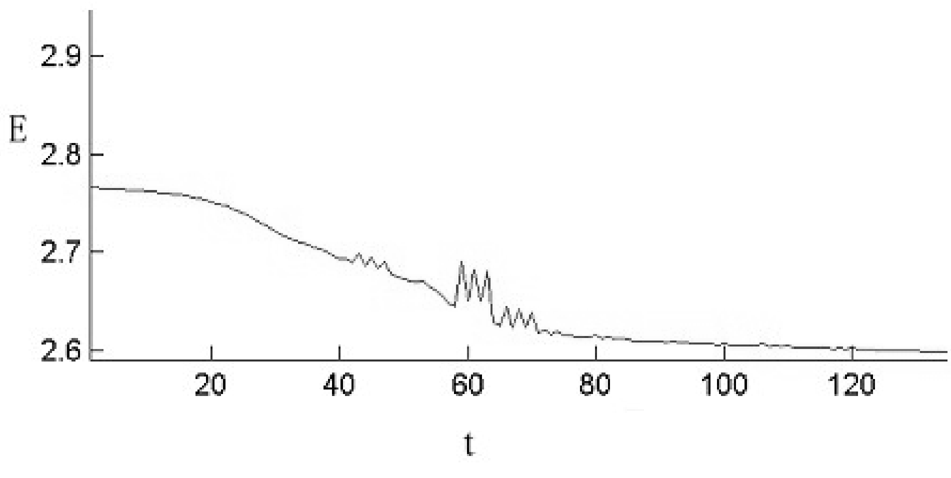

Fig.1. the simulated time evolution of energy function of FHNN for KUNZ4 problem.