Chapter 154
Transiently Chaotic Neural Network with Variable Thresholds for the Frequency Assignment Problem in Satellite Communications

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Abstract We proposed a transiently chaotic neural network with variable thresholds (TCNN-VT) by mapping the optimization problem onto the thresholds in the self-feedback terms of the neural network. This TCNN-VT model consists of $N \times M$ noisy chaotic neurons for an N-carrier-M-segment frequency assignment problem (FAP). The application of this new model on the FAP in satellite communications shows better performance compared with existing techniques, especially in large-scale problem.

Introduction

For the frequency assignment problem (FAP) in satellite communications, Mizuike and Ito [1] divided the carrier to consecutive unit segments and proposed segmentation of frequency band. Funabiki and Nishikawa [2] solved the FAP with a gradual neural network (GNN), where cost optimization is achieved by a gradual expansion scheme and a binary neural network is in charge of the satisfaction of constraints. Salcedo-Sanz *et al.* combined the Hopfield network with simulated annealing (HopSA) [3] and the genetic algorithm (NG) [4] for the FAP. However, as a kind of hybrid algorithms, the computational cost of the HopSA and the NG are increased compared with the GNN [2, 3].

Chen and Aihara [5] proposed a transiently chaotic neural network (TCNN) by introducing transiently chaotic dynamics into the Hopfield neural network (HNN) [6]. With decaying of the self-feedback connection, TCNNs are more effective in solving combinatorial optimization problems compared to the HNN [7]. We further develop the TCNN by proposing a transiently chaotic neural network with variable thresholds (TCNN-VT). The thresholds are designed to minimize the largest interference after frequency rearrangements.

This paper is organized as follows. We propose the TCNN-VT and described the formulation of the TCNN-VT on the FAP in Section "Transiently Chaotic

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Neural Networks with Variable Thresholds.”. Simulation results are presented in Section “Simulation Results and Discussion”. Finally, we conclude this paper in Section “Conclusion”.

Transiently Chaotic Neural Networks with Variable Thresholds

In the self-feedback term of the TCNN [5], the threshold I_0 is constant positive. We propose the TCNN-VT by varying the threshold with the interference of the assignment which firing of the neuron represents and denote it as $I_{ij}^{(0)}$:

$$I_{ij}^{(0)} = 1 - \frac{d_{ij}}{d_{i,max}} \tag{154.1}$$

where d_{ij} is the element on row i column j of the cost matrix D, and $d_{i,max}$ is the maximum value in row i. Cost matrix $D = (d_{ij}, i = 1, \ldots, N; j = 1, \ldots, M)$ is obtained from the interference matrix $E^{(I)}$ [2].
Hence, the new TCNN-VT model is described as:

$$x_{ij}(t) = \frac{1}{1 + e^{-y_{ij}(t)/\varepsilon}} \tag{154.2}$$

$$y_{ij}(t+1) = ky_{ij}(t) + \alpha \left(\sum_{p=1,\, p\neq i}^{N} \sum_{q=1,\, q\neq j}^{M} w_{ijpq} x_{pq}(t) + I \right) - z(t) \left[x_{ij}(t) - I_{ij}^{(0)} \right] \tag{154.3}$$

where x_{ij} and y_{ij} is the output and the internal state of neuron ij, respectively. ε is the steepness parameter of the neuron activity function ($\varepsilon > 0$). k is the damping factor of the nerve membrane ($0 \leq k \leq 1$). w_{ijpq} is the connection weight from neuron ij to neuron pq and is determined [8] by the energy function (154.4). Furthermore, α is the positive scaling parameter for inputs. $z(t)$ is the self-feedback neuronal connection weight ($z(t) \geq 0$), $z(t+1) = (1-\beta)z(t)$. β is the damping factor ($0 \leq \beta \leq 1$). I is a positive input bias.

The objective of the FAP includes two part, i.e., minimization of the largest interference after reassignment and minimization of the total accumulated interference between systems [1, 2, 3]. According to [1, 2, 9], the energy function for the TCNN-VT of the FAP is defined as:

$$E = \frac{W_1}{2} \sum_{i=1}^{N} \left(\sum_{j=1}^{M} x_{ij} - 1 \right)^2 + \frac{W_2}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{\substack{p=1 \\ p\neq i}}^{N} \sum_{q=max(j-c_p+1,1)}^{min(j+c_i-1,M)} x_{ij} x_{pq}$$
$$+ \frac{W_3}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} x_{ij}(1 - x_{ij}) + \frac{W_4}{2} \sum_{i=1}^{N} \sum_{j=1}^{M} d_{ij} x_{ij} \tag{154.4}$$

where $W_i, i = 1, \dots, 4$ are weighting coefficients. The W_1 term forces that every segment in system 2 is assigned to one and at most one segment in system 1. The W_2 term guarantees that all the segments of one carrier in system 2 are assigned to consecutive segments in system 1 in the same order [2]. The W_3 term is used to force neuron outputs to approach 0 or 1 [9]. The W_4 term is needed to optimize the total interference. We convert the continuous output x_{ij} to discrete neuron output x_{ij}^b according to the average value of neuron outputs. If the neuron output x_{ij}^b is 1 at the end of the neuron update, then carrier i is assigned to segment j, and no assignments are made if $x_{ij}^b = 0$.

Simulation Results and Discussions

An iteration is terminated once a feasible assignment is obtained or the number of iteration steps exceeds 15,000. The specifications of the five instances from [2] are listed in Table 154.1.

The choices of these parameters are similar to those used in other optimization problems [5, 7] as follows: $\varepsilon = 0.004$, $k = 0.99$, $\alpha = 0.0015$, $\beta = 0.001$, and $z(0) = 0.1$. Initial inputs $y_{ij}(0)$ are randomly generated from $[-1, 1]$. Values for the weighting coefficients are chosen as follows: $W_1 = 1.0$, $W_2 = 1.0$, $W_3 = 0.7$, $W_4 = 0.00015$. The tuning of these weight coefficients is necessary to obtain better performance.

We run the TCNN-VT on each instance 1, 000 times with different randomly generated initial neuron states. Table 154.2 shows results for every instance, including the largest interference, the total interference, and the convergence rate. The convergence rate is the ratio at which the neural network finds a feasible solution in 1,000 runs. The average iteration steps T and standard deviations are also shown in this Table. The results show that the TCNN-VT is effective in reducing the largest interference and total interference by rearranging the frequency assignment.

Table 154.3 shows and the comparison of the TCNN-VT with the GNN [2] and the HopSA [3]. We show that the TCNN-VT is comparable with the GNN in terms of the largest interference and outperforms the GNN in terms of the total interference. Compared with the HopSA, the TCNN-VT is more efficient.

Table 154.1 Specifications of the FAP instances used in the simulation

Instance	Number of carriers N	Number of segments M	Range of carrier length	Range of interference
1	4	6	1–2	5–55
2	4	6	1–2	1–9
3	10	32	1–8	1–10
4	10	32	1–8	1–100
5	10	32	1–8	1–1000

Table 154.2 The performance of the TCNN-VT on five instances. The interference is shown as the best and average values (Best/ Ave). T is the average number of iteration steps. The convergence rate is the ratio at which the neural network finds a feasible solution in 1,000 runs. "SD" stands for "standard deviation"

Instance	Largest Interference (Best/ Ave)	Total Interference (Best/ Ave)	T mean±SD	Convergence Rate (%)
1	30/ 35.4	100/ 112.6	1191 ± 273	100
2	4/ 4.8	13/ 15.4	1799 ± 317	100
3	7/ 8.4	96/ 130.6	2904 ± 96.5	92.4
4	70/ 94.1	828/ 1145	2716 ± 172.8	89.1
5	661/ 849	6910/ 9527	3075 ± 268	86.6

Table 154.3 Comparison of simulation results (largest interference and total interference) obtained by the TCNN-VT, GNN and HopSA for instances 1 to 5

Instance	GNN [2]		HopSA [3]		TCNN-VT	
	Largest	Total	Largest	Total	Largest	Total
1	30	100	30	100	30	100
2	4	13	4	13	4	13
3	7	85	7	85	7	96
4	64	880	84	886	70	828
5	640	8693	817	6851	661	6910

Conclusions

We proposed a novel approach, i.e., the transiently chaotic neural network with variable thresholds, to solve the FAP in satellite communications. The novel aspect of the TCNN-VT is that the threshold in the self-feedback term of every neuron is dependent on the interference of the frequency assignment which the neuron represents. Compared with other techniques, i.e. the GNN [2] and the HopSA [3], the TCNN-VT is more efficient for the FAP in satellite communications, especially in large-scale problem.

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