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Minimizing interference in satellite communications using transiently chaotic neural networks

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ABSTRACT

The frequency assignment problem (FAP) in satellite communications is solved with transiently chaotic neural networks (TCNN). The objective of this optimization problem is to minimize cochannel interference between two satellite systems by rearranging the frequency assignments. For an N-carrier–M-segment FAP problem, we construct a TCNN consisting of $N \times M$ neurons. The performance of the TCNN is demonstrated through solving a set of benchmark problems, where the TCNN finds comparative if not better solutions as compared to the existing algorithms.

1. Introduction

One important research direction in wireless communication is interference minimization, so as to guarantee a desired level of quality of service. The frequency rearrangement is an effective complement alongside the technique for reducing the interference itself. For both intersystem interference and intrasystem interference [1], frequency rearrangements take advantage of carrier interleaving and are effective in practical situations. Early efforts have focused on various analytical methods for evaluations of cochannel interference [2,3], rather than systematic methods for optimizing frequency assignments and for reducing cochannel interference. Among diverse formulations and objectives of frequency assignment problems (FAP) [4,5], we focus on frequency assignments in satellite communications in this paper. The objective of the satellite FAP is to minimize the cochannel interference between two satellite systems by rearranging the frequency assignments. This NP-complete problem is difficult to solve, especially for large-size problems, but is growing in importance, since we increasingly depend on satellites to fulfill our communications needs.

Some seminal work has been done in this area:

- Mizuike and Ito [1] proposed segmentation of the frequency band and presented a method based on the branch-and-bound approach.
- Funabiki and Nishikawa [6] proposed a gradual neural network (GNN), where the cost optimization is achieved by a gradual expansion scheme and a binary neural network is in charge of constraints in the problem.
- Salcedo-Sanz et al. combined the Hopfield network with simulated annealing (HopSA) [7] and the genetic algorithm (NG) [8] to solve the problem.

On another hand, in the development history of modern computation technology, bio-inspired neural networks [9], due to their intrinsic operation functions, have played a very important role. Derived from some aspects of neurobiology and

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adapted to integrated circuits, neural networks have been used widely in various fields such as optimization, linear and nonlinear programming, pattern recognition [10–12] and so on.

On the basis of Hopfield neural networks (HNN) [13,14], chaotic neural networks were presented by Nozawa [15,16] through adding negative self-feedback connections into Hopfield networks. The simulation for several combinatorial optimization problems showed that chaotic search is efficient in approaching the global optimum or sub-optima. As a kind of complicated nonlinear dynamics, chaos has been widely investigated by not only mathematicians and physicists, but also engineers, economists, and scientists from various disciplines [17–19]. Chaotic dynamics have several special characteristics, such as:

1. a sensitivity to initial conditions,
2. determinism, as the system function is well defined,
3. long term unpredictability.

Chaotic dynamics [20] is a complex behavior which can be generated by a finite set of deterministic nonlinear equations with a simple system. Chaos is globally stable and locally unstable [21]. A lot of research in recent years has focused on developing techniques to harness chaos when it is undesirable or to generate chaos so that the useful function of a chaotic system can be utilized. Chen and Aihara [22] proposed a transiently chaotic neural network (TCNN) by introducing a decaying negative self-feedback. The dynamics of the new model are characterized as transient chaos. Numerical experiments on the traveling salesman problem (TSP) and the maintenance scheduling problem showed that the TCNN has high efficiency for converging to globally optimal solutions.

The TCNN, which is also known as chaotic simulated annealing [10], is not problem-specific but a powerful general method for addressing combinatorial optimization problems (COPs) [23–25]. With autonomous decreases of the self-feedback connection, TCNNs are more effective in solving COPs compared to the HNN. In this paper, we solve the FAP in satellite communications through the TCNN, and simulation results show that the performance of the TCNN is comparative with existing heuristics.

This paper is organized as follows. We review the TCNN in Section 2. The formulation of the TCNN on the FAP is described in Section 3. Parameter settings and simulation results are presented in Section 4. Finally, we conclude the contribution of this paper in Section 5.

2. Transiently chaotic neural networks

The TCNN [22] model is described as follows:

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

$$y_{ij}(t+1) \ = \ ky_{ij}(t) + \alpha \left[\sum_{p=1,p\neq i}^{N} \sum_{q=1,q\neq j}^{M} w_{ijpq} x_{pq}(t) + I_{ij} \right] - z(t) \left[x_{ij}(t) - I_0 \right] \tag{2}$$

$$z(t+1) = (1-\beta) z(t) \tag{3}$$

where the variables are:

- y_{ij} internal state of neuron ij;
- x_{ij} output of neuron ij;
- ε the steepness parameter of the transfer function ($\varepsilon \geq 0$);
- k damping factor of the nerve membrane ($0 \leq k \leq 1$);
- α the positive scaling parameter for inputs;
- w_{ijpq} the weight of connection from neuron ij to neuron pq;
- I_{ij} input bias of neuron ij;
- $z(t)$ self-feedback neuronal connection weight ($z(t) \geq 0$);
- I_0 positive parameter;
- β damping factor for the time-dependent neuronal self-coupling ($0 \leq \beta \leq 1$).

w_{ijpq} is confined to the following conditions [14]:

$$\sum_{p=1,p\neq i}^{N} \sum_{q=1,q\neq j}^{M} w_{ijpq} x_{pq}(t) + I_{ij} = -\partial E / \partial x_{ij} \tag{4}$$

where E denotes the energy function, which is designed to have the minimum value at the optimal solution of the combinatorial optimization problem. Weights of connection between neurons (w_{ijpq}) are derived by Eq. (4) so that the energy function will decrease monotonically as neurons update after the self-feedback interaction vanishes ($z = 0$).