The Implementation of A Routing Algorithm Based on Chaotic Neural Network in Multicast Routing Problems[1]

Yingying Yin, Liang Sun, Xiaogang Ruan

Institute of Information and Control,
Beijing University of Technology, 100022, Beijing
gydlpp@163.com；sunliang@bjut.edu.cn；rxgad@bjut.edu.cn

Abstract

The paper studies the problem of constructing multicast trees to meet the quality of service requirements of real-time interactive applications operating in high-speed packet-switched environments. A new delay and delay variation constrained energy function is proposed and adopted to chaotic neural networks to solve QoS multicast routing problem. The emulation verifies that the energy function has an excellent optimization effect, can efficiently draw neural networks to an energy minimum which is corresponding to the optimal result of QoS multicast routing problem.
keyword:multicast rooting chaotic neural networks energy function

1 Introduction

In the past, most of the applications were unicast in nature, i.e., they involved a pair of users and none of them had any quality of service (QoS) requirements. Thus simple routing algorithms, which were mainly concerned with connectivity, were developed based on the network topology. The situation is, however, different now with emerging real-time multimedia applications like digital audio and video. These applications express their QoS requirements in terms of bound on end-to-end delay, packet loss probability etc. Routing algorithm, while making a routing decision, should consider the QoS needs of an application in order to make an efficient use of network resources. In recent years, there has been an effort, at both the algorithm and protocol levels, to develop multicast mechanisms which meet the QoS needs of the emerging real-time multimedia applications and scale well to large network sizes.

The main goal in developing multicast routing algorithm is to minimize the communication resources used by the multicast session. This is achieved by minimizing the cost of the multicast tree, which is the sum of the costs of the edges in the multicast tree. The least cost tree is known as the minimum Steiner tree. The problem of finding the minimum Steiner tree is known to be NP-complete. A number of heuristics are available to find a sub-optimum but “good” multicast tree in polynomial time. The simplest approach of finding a multicast tree is to find the shortest paths from the source to each destination separately and then merge the resulting paths to form a tree. We will refer to this heuristic as the shortest path heuristic.

There are several other heuristics that try to reduce the cost of the tree by increasing the shared portion of the path. The best known heuristics were proposed by Kou et al. (KMB heuristic), Takahashi and Matsuyama (TM heuristic), and Rayward–Smith (RS heuristic)

In this paper, we intend to study the delay and delay variation constrained multicast routing problem, which is an equivalent of the Constrained Steiner Tree(CST) problem in the graph theory. This paper proposed a new way to construct delay and delay variation constrained Steiner minimum tree based on chaotic neural networks. The emulation verified its feasibility and validity.

2 Chaotic Neural Network

Reference[2] proposed a new chaotic neural network model based on transient chaos and time-variant gain(NNTCTG), as defined below. Compared to conventional neural networks only with point attractors, the proposed neural network has richer and more flexible dynamics which are expected to have higher ability of searching for globally optimal or near-optimal solutions. After going through an inverse-bifurcation process, the neural network gradually approaches to a conventional Hopfield neural network starting from a good initial state.

$$y_i(t+1) = ky_i(t) + \alpha\left[\sum_{\substack{j=1 \\ j\neq 1}}^{n} w_{ij}x_j(t) + I_i\right] - z_{i(t)}(x_i(t) - I_0) \tag{1}$$

$$z_i(t+1) = (1-\beta)z_i(t) \tag{2}$$

$$\varepsilon_i(t+1) = (1-\gamma)\varepsilon_i(t) \tag{3}$$

Where x_i, y_i and I_i are output, internal state and input bias of neuron I, w_{ij} is connection weight from neuron j to neuron i, α=positive scaling parameter for input, k= damping factor of nerve membrane($(0 \le k \le 1)$, $z_i(t)$=self-feedback connection weight $(z_i(t) \ge 0)$.β=damping factor of the time-dependent $z_i(t)$, $(0 \le \beta \le 1)$. $\varepsilon_i(t)$=gain parameter of the output function $(\varepsilon_i(t) \ge 0)$, γ =damping factor of the time-dependent $\varepsilon_i(t)$ $(0 \le \gamma \le 1)$.

NNTCTG actually has transiently chaotic dynamics which eventually converge to a stable equilibrium point through successive bifurcations like a route of reversed period-doubling bifurcations, with the temporal evolution of $z_i(t)$ and $\varepsilon_i(t)$ by in (3). Actually, the damping of $z_i(t)$ and $\varepsilon_i(t)$ produces successive bifurcations so that the neurodynamics eventually converge from strange attractors to a stable equilibrium point, as shown in figure 1.

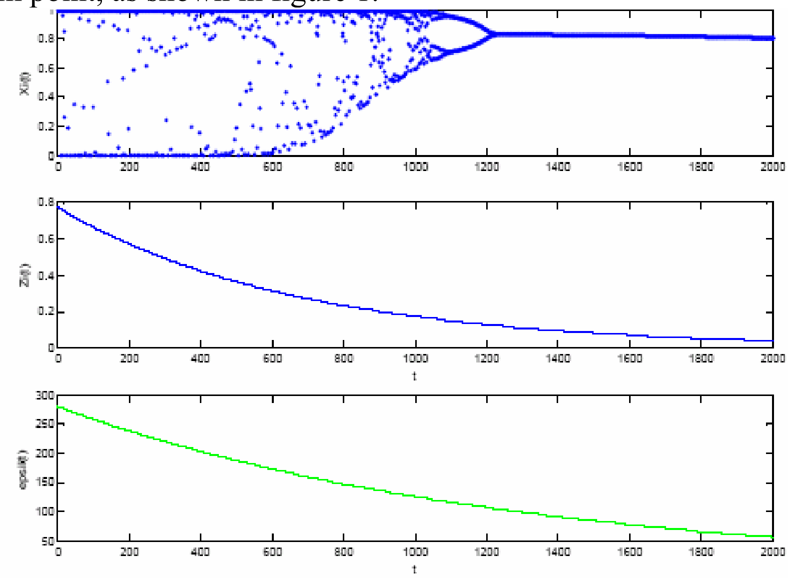


Fig. 1. The evolution of single neuron of NNTCTG. Parameter setting: $k = 0.95, \varepsilon(0) = 280, \beta = 0.0015, \gamma = 0.0008, I_0 = 0.84, z_0 = 0.77$

3 Multicast Routing Algorithm Based on NNTCTG

3.1 The Mathematical Model of the Problem

The delay and delay variation constrained QoS multicast routing problem is to find the delay and delay variation constrained best route in a distributed network. A point-to-point communication network is represented as a directed graph $G=(V,E)$, with node set *V* and edge set *E*. Each link $l=(u,v)$ between a pair of nodes is an outgoing link from *u* that terminates at *v*. We denote the cost and delay associated with every link by C_l and F_l respectively. The link cost may be either monetary cost or some measure of the resource utilization at the link. The link delay may consist of queuing delay, transmission delay and propagation delay.

Supposing there is a multicast demand in the network, with *s* as the source node and N destination nodes $D \in V - \{s\}$. The multicast tree requires the biggest delay value T_{max} to be as small as possible, namely the delay value from source node to each destination node to be around T_{max}. Thus, for $\forall u,v \in D, and \cdot \mathrm{u} \neq \mathrm{v}$,the delay variation constraint.

$$\left|\sum_{l\in P_T(s,v)} F_l - \sum_{l\in P_T(s,u)} F_l\right| \le \xi \quad \textbf{(4)}$$

can be transformed to the delay constraint

$$T_{\max} - \xi < \sum_{l\in P_T(s,u)} F_l < T_{\max} \quad \textbf{(5)}$$

Actually, we can start from $T_{\max}$ ($T_{\max}(0)=\Delta, \Delta$ as the biggest delay value), to find the minimum Steiner tree with a delay value between $[T_{\max}-\xi, T_{\max}]$, and then gradually reduce $T_{\max}$ by η ($\eta=\min(T_u - T_v)$, $u,v \in \{availabler \cdot route\}$,and T_u, T_v represent the delay value of the available routes) to the least delay value of the available routes. And select the multicast tree with the least cost as the final one. Thus, we can find the minimum multicast tree satisfying less delay constraint while at the same time the delay variation constraint.

First, for every $d_i \in D$, compute M available routes with comparatively less cost to construct a $N \times M$ marshal Ω of available routes. M should not be too small, as to ensure that there at least would be one route satisfying the delay constraint in the M available routes for each destination node. We denote the cost and delay value associated with every route by C_{ij} and T_{ij} respectively. A $N \times M$ planar chaotic neural network is used to correspond to the routes in Ω, with the steady output of each neuron "0" or "1". V_{ij}, the output of the neuron in the *i*th row and the *j*th line, is 1 when the *j*th route is selected for the destination d_i, otherwise 0. COST represents the cost of the multicast tree. Optimization problem can be transformed into following constrained problem.

Already known: the available marshal route Ω

Compute: $V=\{V_{00}, V_{01,} \cdots, \mathrm{V}_{0,\mathrm{M-1}}, \cdots, V_{N-1,0}, V_{N-1,1}, \cdots, V_{N-1,M-1}\}$

Target function: $Min(Cost)$

Restriction: $\sum_j V_{ij} = 1$; $V_{ij} \in \{0,1\}$;

$$T_{\max} - \xi < \sum_j T_{ij} V_{ij} < T_{\max}$$

3.2 Description of the Algorithm

The steps of the algorithm is given according to the mathematical model and the network model of the problem discussed above:

First: find M routes with the least cost from source node s to each destination node d_i ($i = \{1,2,\cdots,N\}$) with Dijkstra kth shortest route, and at least one route should satisfy the delay constraint.

Second: construct a $N \times M$ planar chaotic neural network , from which N routes are selected. Only one route for each destination node is chosen and should satisfy the delay constraint.

4 Energy Function

The most important part of neuron network for solving QoS NP complete problem is the set of energy function. Energy function must satisfy two requirements: first, it must include the description of the excellent solution and the restrictions of the problem, and the excellent solution corresponding to the minimum value of the energy function; second, it must find the valid solution in acceptable cycles, which involves the setting of the parameters of the energy function.

4.1 The Original Energy Function

NNTCTG energy function is constructed as follows according to the routing goal:

(1) optimization of the multicast tree cost

$$E_1 = \sum_{i=0}^{N-1} \sum_{\substack{j=0 \\ j \neq 1}}^{M-1} \sum_{\substack{p=0 \\ p \neq 1}}^{N-1} \sum_{q=0}^{M-1} V_{ij} V_{pq} \sum_{k=1}^{K} C_k (L_{ijk} \oplus L_{pqk}) \tag{6}$$

C_k represents the cost of the kth link. $L_{ijk} = 1$ when the kth link is on the jth path with d_i as the destination node, otherwise 0. $\oplus$ is the "or" Boolean calculation.

(2)

$$E_2 = \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \sum_{\substack{q=0 \\ q \neq j}}^{M-1} V_{ij} V_{iq} \tag{7}$$

Its purpose is to ensure that there shall be at most one "1" in every row. But when all outputs of the neurons are "0", the E_2 can also be minimum, so the following restriction formula is needed.

(3)

$$E_3 = \frac{1}{2} \sum_{i=0}^{N-1} \left(\sum_{j=0}^{M-1} V_{ij} - 1 \right)^2 \tag{8}$$

(4)

$$E_4 = \frac{\mu_4}{2} \sum_{i=1}^{N} \left(\sum_{j=1}^{M} T_{ij} V_{ij} - T_{\max} \right)^2 \bullet \left(\sum_{j=1}^{M} T_{ij} V_{ij} - T_{\max} \right) \tag{9}$$

$$z_i = \left(\sum_{j=1}^{M} T_{ij} V_{ij} - T_{\max} \right) \tag{10}$$

We can know from the above formula that this is a delay bounded restriction, and its delay variation constraint is realized in such way: starting from $T_{\max}$ to find the Steiner tree with delay value between $[T_{\max} - \xi, T_{\max}]$. Reducing the value of $T_{\max}$ gradually and at last compare the Steiner trees with different delay bounds to choose the Steiner tree with the least cost as the final multicast tree.

4.2 Improved Energy Function

We made a rational improvement based on the forth energy function, which satisfied both the delay and delay variation constraint.

$$E_4 = \frac{1}{2}\sum_{i=1}^{N} H(z_i) \tag{11}$$

$$H(z) = \begin{cases} \mu_{41} z^2, z > 0 \\ 0, -\xi \le z \le 0 \\ \mu_{42} z^2, otherwise \end{cases} \tag{12}$$

Where the main function of μ_{41} is to punish severely the routes that do not satisfy the delay constraint, while the main function of μ_{42} is to punish lightly the routes that satisfy the delay constraint but not the delay variation constraint. Thus, the whole energy function E can be set in this way:

$$E = \mu_1 E_1 + \mu_2 E_2 + \mu_3 E_3 + E_4 \tag{13}$$

The parameters of E_4 are included in the formula. μ_1, μ_2, μ_3 are the punishment parameters of the energy function. μ_{41}、μ_{42} are also punishment parameters but they are not included in the above formula. The parameters are different according to the networks and different problem sizes. Their relative value is fixed on in accordance with their relative importance for the energy function.

5 Analysis of Simulation Results and Conclusion

5.1 Simulation of Networks

For convenience, we choose the QoS multicast route topology in reference[1](figure 2) as simulation object, where node 1 with saturated colour is the source node, nodes 3,5,7 with light colour are the destination nodes. And the 12 links are numbered.

The network parameters:

$$k = 0.95, \varepsilon(0) = 280, I_0 = 0.5, z(0) = 0.0095, \beta = 0.007, \gamma = 0.04$$

$$\alpha = 0.015, \mu_1 = 5, \mu_2 = 5.5, \mu_3 = 55.0, \mu_{41} = 50, \mu_{42} = 1$$

We apply the chaotic neuron network with the new energy function in the network of reference[1]. The multicast tree with three destination nodes is shown in figure 3, when the maximum delay $T_{\max} = 5.0$,and the maximum delay variation value ξ =1.0, with the total cost 6. The Steiner tree is shown in figure 5 for the topology network of figure 4, when the maximum delay $T_{\max} = 7.0$,and the maximum delay variation value ξ =1.0, with a total cost 8. And the Steiner tree is shown in figure 7 for the topology network of figure 6, with maximum delay $T_{\max} = 6.0$ and the maximum delay variation ξ =2.0, cost 8.

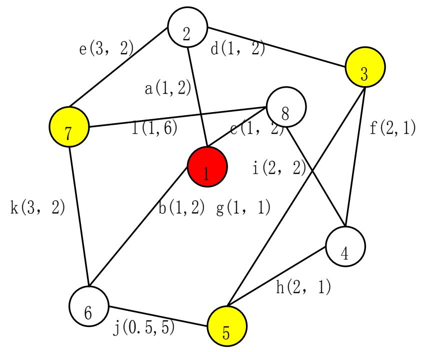


Fig. 2. The topology of network

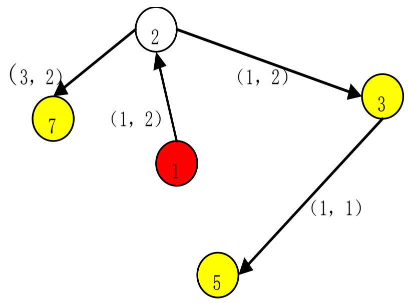


Fig. 3. The optimal multicast tree

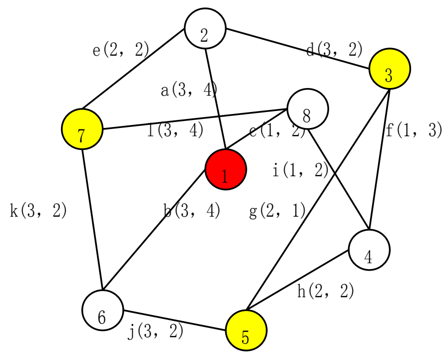


Fig.4. The topology of network

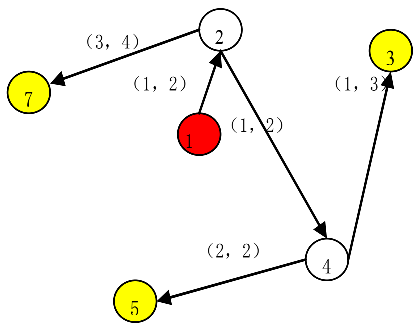


Fig. 5 the optimal multicast tree

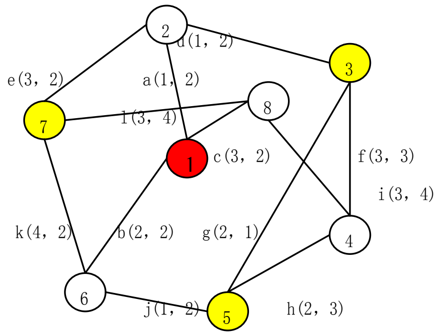


Fig.6. The topology of network

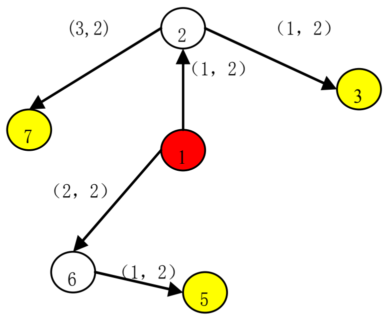


Fig. 7. The optimal multicast tree

5.2 Comparison of the Algorithm with the improved energy function and the Algorithm of Reference[1]

We compared the chaotic neuron network with the improved energy function and that used in reference[1]. Changing the number of destination nodes, simulating 370 times for each optimization algorithm, and get the average excellence rates and compare them by running 100 times for each algorithm. We can see from figure 8 that the excellence rates do not change markedly with the increase of destination nodes, while the algorithm of this paper is better than that of reference[1] by 20%.

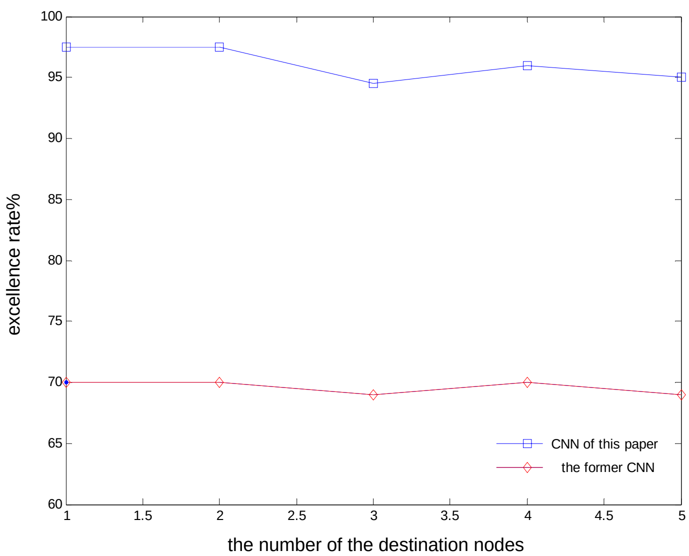
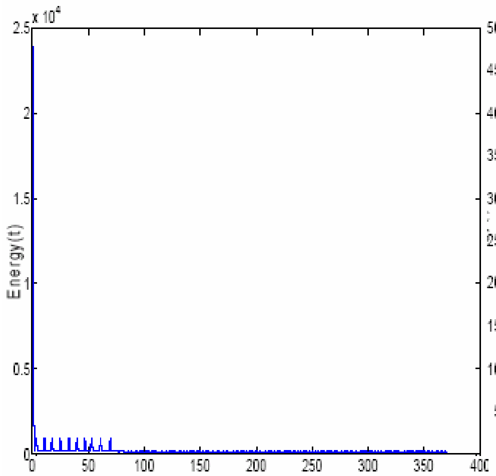


Fig.8. The relationship between the number of destination nodes and the excellence rate

We can see from the above test that the excellence rate is enhanced by more than 20% for the same topology of network and parameters. The main reason is the improvement of the delay and delay variation constraint in the energy function, which effectively eliminates both of the routes that do not satisfy the delay constraint in the rough search and the ones that do not satisfy the delay variation constraint in the careful search.

For the searching time, we can get excellent results with comparatively small cost by just 300 iterations. It must be noted that the iteration time is not determined by the comparison of the energy function's variation, for there is still some variations when the chaotic neuron network converges to the optimal solution. In QoS energy function model, the energy function is characterised by drastic attenuation. Certain chaos is added after many illegal solutions is eliminated for careful search in the legal solutions. Since the legal solutions are far less than the illegal solutions, the attenuation is still not calmed down when the optimal result is got. As shown in figure 9 and 10, the variation of the energy function is small against the total energy function of the whole neuron network and not sufficient to get the network from one solution to another one.

It can be seen from the simulation that the enactment of energy function and its destination item and constraint item must comply with the concrete constraints of the concrete problems. The way to set constraints and to restrict the neurons can all affect the reflection of the energy function for the problem, and indirectly affect the optimization effect of the neuron network.



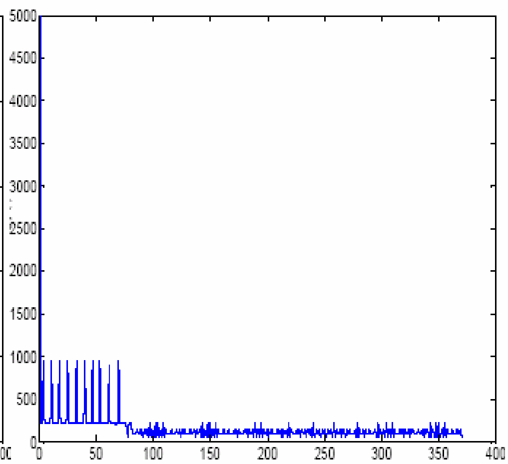


Fig. 9. The energy function of simulation 3 **Fig.10** The energy function below 5000

References

[1] Zhang Su-Bing Liu Ze-Min A New Multicast Routing Algorithm Based on Chaotic Neural Networks Chinese Journal of Computers Dec 2001 Vol 24 No 12

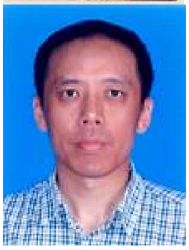
[2] Tan Y, Deng C, He Z Y. Chaotic annealing neural networks and its application to direction estimation of spatial signal sources In: P roc IEEE Workshop on Neural Networks for Signal Processing, Florida, USA , 1997, 7: 541- 550

[3] Cavendish D, FeiA , GerlaM *et al*. On the maintenance of low cost multicast trees with band width reservation. In: Proc Internet Mini-Conference with Globcom98, Australia, 1998

[4] Weng Miaofeng Gao Jing Chaotic Neural Network Based On Annealing Strategy and Their Application to TSP . Minimicro System May 2002 Vol 23 No 5

Yingying Yin, 1980--, female, Han nationality, Langfang city, Hebei province, master degree. Institute of Information and Control, Beijing University of Technology.Majoring on the study of Optimization.

Liang Sun, 1951--,male, Han nationality, doctor degree. Institute of Information and Control, Beijing University of Technology, majoring on control theory.



Xiaogang Ruan, 1958--,male, Han nationality, Beijing, doctor degree, professor,tutor of doctor. Institute of Information and Control, Beijing University of Technology,majoring on biology computing and computing intelligence, auto-control and intelligent information processing.