Simulated Annealing and Genetic Algorithms Based for Image Segment with Partially Evolved Hopfield Neural Network

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Abstract A combined optimization of genetic algorithms with simulated annealing has been applied to image segmentation with good results in this paper. The defect of Hopfield neural network is being captured by local optimal solutions, while the defect of genetic algorithms is the low speed of convergence. Both disadvantages mentioned above have been overcome here. Solutions obtained with the converged Hopfield neural network are applied to the genetic algorithm to search for the optimization on the plane of threshold value.

Keywords Hopfield neural network. Simulated annealing. Genetic algorithms. Optimization

1. Introduction

Image segment is a classical difficult problem in the digital image process, it can be turned into the optimization of segment threshold value plane of the image. Applied extensively to the field of pattern-recognition, image process[1] , optimization, etc. Hopfield network have offered even wider development space and better solution for solving these problems. However, Hopfield network without solidity[2] , may fall into local minimum because of calculating energy function while dropping in energy. When the network size becomes greater, energy function becomes more complicated, this kind of question becomes more severe. The methods, which can be used to raise the solidity of the Hopfield neural network, are mainly as follows:

① To affiliate the trap-escape algorithms for Hopfield network. The typical method joins perturbation LEM method[3] for converged Hopfield network. If the network energy can be reduced after the perturbation, the network may jump out of the present local minimum trap. But in the Hopfield network state space, if the overall energy spot far away from local minimum trap, the ability that the perturbation algorithm flees from local minimum trap is very limited.

②To adopt genetic algorithm to evolve Hopfield network[4]. The advantage of the genetic algorithm overall seeking the optimization with excellent ability, can be utilized to raise the ability of restraining to the optimum state of the overall situation of Hopfield network. But the genetic algorithm has the problem of "premature convergence", and when Hopfield is very large in network size, it is relatively slow.

③ To join the thermodynamics system when Hopfield network energy drops. The Hopfield network sometimes accept energy rise by simulated annealing algorithm, may jump out of local minimum trap. But simulated annealing tactics may make the network fall into another after jumping out of one local minimum trap.

Inspired by partially evolved Hopfield network, we choose local region, in the iteratively converged Hopfield network at random, to form some new small-scale Hopfield networks, and adopt simulated annealing and genetic algorithm combined to optimize those networks. If these small-scale Hopfield networks' energy function value are reduced in the course of evolution, we get their input and output state back to the whole Hopfield network, and iterate the state equation of the neural network again, to reduce the energy function value of the whole neural network till its convergence[5]. So, while raising the ability of the Hopfield network to overall optimum, we accelerate the speed of the whole algorithm by reducing computational complexity.

2.Principle of the algorithm and its realization

2. 1 Partially evolved Hopfield neural network

At present, Hopfield network is the most abundantly studied and most widely applied feedback neural network[6], figuring symmetrical connections between neurons. We suppose, the network is made up of two-dimensional neuron array to set up Hopfield network $\{(i,j)\}$; $i\in[1,N]$ $j\in[1,M]\}$, among them, N and M represent the neuron amount of abscissa and ordinate respectively. V_{ij} and U_{ij} represent the output and input state of the neuron(i, j)respectively, while $W_{ij,kl}$ represent the connection weight coefficient of the neuron (k , l) from the neuron (i , j). The output of the neuron(i, j) is determined by other neurons' output and some offset I_{ij}, so its iterative state equation is

$$C_{ij}\frac{dU_{ij}}{dt} = -\frac{U_{ij}}{R_{ij}} + \sum_{k=1}^{N}\sum_{l=1}^{M} W_{ij,kl}V_{kl} + I_{ij} \quad (1)$$

Among them, C_{ij} and R_{ij} are the defined parameters in advance, and

$$V_{ij} = g(\frac{U_{ij}}{U_0}) = \frac{1}{2}(1+\tan\frac{U_{ij}}{U_0}) \quad (2)$$

Among them, U_0 is a constant. The energy function of Hopfield network can show

$$E = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{N}\sum_{l=1}^{M} W_{ij,kl}V_{ij}V_{kl} - \sum_{i=1}^{N}\sum_{j=1}^{M} V_{ij}I_{ij} + \sum_{i=1}^{N}\sum_{j=1}^{M}\int_0^{V_{ij}} g^{-1}(V)dV \quad (3)$$

When $C_{ij}>0$, $W_{ij,kl}=W_{kl,ij}$ and $i,k\in[1,N]$&$j,l\in[1,M]$existed, Hopfield network is a steady system and the input and output of each neuron will iteratively converge to a steady state by equations (1)and(2).

Referring the optimizing problem of the threshold value plane by Hopfield network, each pixel in the two-dimensional pixel matrix of the image correspond to a certain neuron in the two-dimensional neuron matrix of Hopfield network one by one, while the border pixel correspond to initial output value of a certain neuron. This value is equal to its grey level of normalization, and will be kept all the time.

Simulated annealing and genetic (SAG) algorithm optimizes local region chosen from Hopfield network while calculating separately, choosing some different local regions to optimize separately. There are three principles: (1)To choose local region at random; (2)To batch local regions, only optimize one region each time; (3) The energy of the whole network is reduced as that of local regions is reduced.

We suppose a N×M neuron matrix Q as a Hopfield network, $W_{ij,kl}$ and I_{ij}（i，j）∈Q. It can be divided into K local regions $\{Q^{(1)},Q^{(2)},\cdots,Q^{(K)}\}$which match the criteria:

$Q^{(k)}\cap Q^{(s)}=\circ$, $r\neq s$, r,s=1,2,…,K

$Q^{(1)}\cup Q^{(2)}\cup\ldots\cup Q^{(k)}=Q$

The energy function to a sub Hopfield network in a random local region $Q^{(r)}$ is:

$$E^{(r)} = -\frac{1}{2}\sum_{(i,j)\in Q^{(r)}}\sum_{(k,l)\in Q^{(r)}} W_{ij,kl}^{(r)}V_{ij}V_{kl} - \sum_{(i,j)\in Q^{(r)}} V_{ij}I_{ij}^{(r)} + \sum_{(i,j)\in Q^{(r)}}\int_0^{V_{ij}} g^{-1}(V)dv \quad (4)$$

The energy function to the Hopfield network can be:

$$E = E^{(r)} - \frac{1}{2}\sum_{(i,j)\in(Q-Q^{(r)})}\sum_{(k,l)\in(Q-Q^{(r)})} W_{ij,kl}V_{ij}V_{kl} - \sum_{(i,j)\in(Q-Q^{(r)})} V_{ij}I_{ij} + \sum_{(i,j)\in(Q-Q^{(r)})}\int_0^{V_{ij}} g^{-1}(V)dv \quad (5)$$

When the output state of the neuron in region（$Q-Q^{(r)}$ does not change, the energy of the whole network will reduce with that of sub Hopfield network in local region. So the whole network will jump out of the possible local optimum trap, reducing the amount of calculation greatly.

2.2 Simulated Annealing and Genetic(SAG) Algorithms

The most serious problem of traditional genetic algorithms is premature convergence. Because of the limitation of the population and proportional selection according to adaptability, the traditional mechanism enables the pattern higher than average to obtain more samples in the next generation. Once some pattern samples was held the superiority in the population, that can be strengthened by the tradition genetic algorithms. That will strict the hunting zone rapidly. The population rapidly converged, does not necessarily achieve the overall optimum. Premature convergence occurs[6,7].

In order to enhance the overall convergence rate, we combine the simulation annealing strategy in the genetic algorithms. The simulation annealing algorithm adopts the Metropolis criterion, and stochastically creates a new candidate solution each step in algorithm. If this new solution reduces the objective function, it is acceptable; otherwise it must be decided by the index probability whether it can be accepted. The probability of the new solution P is given by the following formula:

$$P = \begin{cases} \exp(-\Delta f/T) & \Delta f > 0 \\ 1 & \Delta f \le 0 \end{cases} \quad (6)$$

Among them, Δf is the objective function change caused by the stochastic perturbation, T is the control parameter, which is equal to the temperature in thermodynamics. After concreting this kind of thought, we draw SGA algorithm flow as figure 1 shows.

Explanation for the program and choice of the control parameter:

1)Initialization of the population: $i=0, T=T_0$. We initialize the population x (0) with stochastic method, and calculate its compatibility. T_0 is the initial temperature. In order to guarantee $\exp(\Delta f/T_0)\approx 1$, we choose $T_0=10(f_{max}-f_{min})$. Generally, the final temperature T_{final} adopt a minimum that approach to 0, as the termination condition. Namely, $\exp(\Delta f/T)\to 0$ algorithms converge to the optimal solution.

2)Genetic algorithm: We choose n individual strings with high adaptability as parents, and use overlapping, mutant operator for each parent P_1, P_2 to product filial generation C_1, C_2, then calculate the compatibility of C_1, C_2. If $f_{Ci}>f_{Pi}$, i=1、2replaces P_i with C_i. Otherwise, maintains Pi with the probability $\exp((f_{ci}-f_{pi})/T)$.

3)$i=i+1$, if $i\leqslant$Constant, return. Constant is the internal recycling times. If the objective function changes very little with continuously searches for many times, we can consider the system tends to the thermal equilibrium.

4)To reduce the value of T according to the temperature attenuation regulation: We choose linear function $T(k+1)=\beta T(k)$,among them 0< β <1. The temperature drops more slowly, if β is more close to 1.

The algorithm will certainly converge to the optimal solution, as long as the control parameters are reasonable.

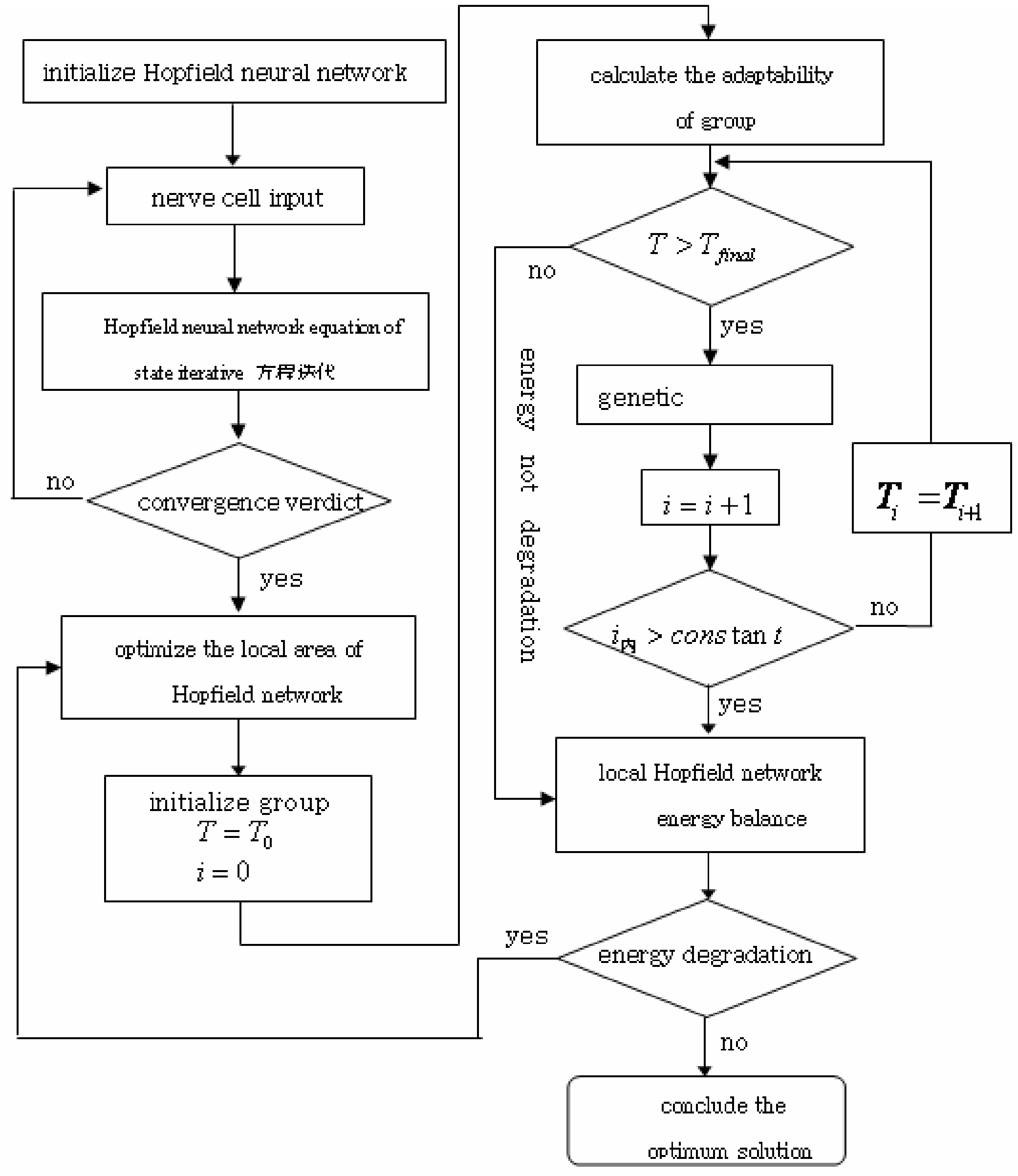

Figure 1 The SAG algorithm flow of partially evolved Hopfield neural network

3. Test Result

We use PⅣ4800/2.6G/256M microcomputer to carry on the calculation of threshold value optimization of the image segment, and compile the program with Matlab. Figure 2 shows the primitive Lena image, 256*256 pixels, with the grey rank [0, 255]. In the test, we adopted three different algorithms to optimize the image, which respectively were: the Hopfield nerve network, the genetic algorithms and partially evolved Hopfield nerve network with the annealing strategy, proposed in this article. Control parameters of each algorithm are:

（1）Hopfield network: Control parameter for each neuron establishes: I_{ij}=0.5，C_{ij}=1.414，R_{ij}=0.5，U_0=50。The input value for every neuron varies in [-100,100] stochastically.

（2）Genetic algorithms: When we only adopt the genetic algorithms to evolve network, the community scale is 100 bodies, overlapping rate .P_c=0.1, variation rate P_m=0.02.

（3）partially evolved Hopfield nerve network with the annealing strategy: To obtain the high grade solutions, control parameter T_0 of annealing strategy should be great enough. Considering the complexity request on the other hand, we choose initial temperature T_0=100，final temperature T_{final}=1. The coefficient of attenuation takes β=0.9 according to the experience. We adjust the internal recycling times by the experimental effect, Constant=10. The parameters of Hopfield network and the genetic algorithms establishment is the same as (1) (2) separately.

Figure 2 Lena

Figure 3 Segment result of Hopfield network

Figure 4 Segment result of GA and SAG

Table 1 has listed the average result of each algorithm which divides figure 2 for 100 times.

Table 1 The average result of each algorithm which divides figure 2 for 100 times

	Hopfield Network	GA	Algorithm of this paper
convergence rate(%)	92	100	100
iteration times of	208G	32174G	285G
speed (s)	2.25	2056.86	8.41

As the result demonstrates, although converged quickly, Hopfield neural network is actually easy to fall into the local optimum. However, the amount of calculation is far more complex than other algorithms, if we only adopt genetic algorithms. The genetic algorithms with the annealing strategy enable the search for the region with higher expected value, which contains the optimum, to be more effective, so that enhance the search ability. At the same time, the partially evolved Hopfield neuronal network converges rapidly, so the amount of calculation is not that great.

4. Conclusion

The genetic algorithms and the simulated annealing algorithms are new branches, following the natural law of computation. They fit basic rules of the natural sciences and its branches that affect and seeps mutually. Inspired by this thought, we introduce simulated annealing and genetic algorithm combined for the partial evolution Hopfield neuronal network, to carry on the image segment. The algorithm calibrates the degree of adaptability in the exponential form, uses the floating number code, scale selection operator according to qualification, the arithmetic overlapping operator, the non-even mutant operator, as well as the superior-preserved strategy. After the compliment of each generation, we carry on perturbation for one time in the neighborhood of each body, and accept the new solution according to the Metroplis criterion in the simulated annealing strategy. The search ability of the simple genetic algorithm has been enormously strengthened by joining the simulated annealing algorithm. Meanwhile, we selects the local regions of Hopfield neuronal network to reduce the amount of calculation and to accelerate the convergence speed. Finally, we do the simulation with Matlab, and build the foundation for further studies.

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