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COLLECTIVE COMPUTATION OF NEURAL NETWORK

by

Yao Guozheng, Wang Yunjiu

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COLLECTIVE COMPUTATION OF NEURAL NETWORK

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ABSTRACT

Computational neuroscience is a new branch of neuroscience originating from current research on the theory of computer vision. The goal of the branch is to find a new interdisciplinary approach to dealing with information processing in the brain. The research involves scientists working in artificial intelligence engineering and neuroscience. The paper introduces the collective computational properties of model neural networks, mainly in a theoretical framework of the study of neural network computational properties advanced by Hopfield and its application to vision research. On this basis, the authors analyzed the significance of the Hopfield model.

Key phrases: Computational Neuroscience, Neural Network, Model Ciruit, ~~and~~ Dynamics of Neural Network, Chinese Translated

I. Foreword

The authors pointed out the following [1]: with the central topic of visual information processing, computer vision not only creates conditions for our overall understanding of human vision in biointelligence, but also establishes a theoretical basis for developing an automatic graphic analysis system, thus making research on vision the vanguard in the investigation of brain information processing.

Now what sort of computation can the nervous system engage in? In discussing this kind of problem, the obviously correct answer is to be expected only within the computational theory framework of Marr [2-3], because this theory specifies the general goal of computational neuroscience. In other words, in dealing with specific problems that a neural network should solve, not only should a researcher decide the input image with the expectation of the output form, but he also should decide the algorithm for execution by this neural hardware in computation in order to solve this problem. Hence, computational neuroscience especially stresses how the neural hardware executes computations using an algorithm. In other words, this approach stresses the properties of a single neuron, the synaptic connections between neurons, the dynamic properties of the neural network, and how the execution can lead to a special algorithm for execution.

However, often researchers do not directly study the bioneural network; they study a model neural network. The reason is very simple. The bioneuron is a continuously dynamic system. There are a large number of connection lines among neurons, forming a large number of synaptic connections. Therefore, this is very difficult with redoubled efforts but limited results, when using only traditional neuroscientific methods to study the computational properties of the bioneural network. On the other hand, it does not do justice to reality to describe in detail, from random sampling of synaptic connections and neuronal activity, how a neural network computes: what sort of computation does the neural network do? Based on Marr's computational theory, we should distinguish between the abstract theoretical level and the real neural mechanism. It is unrealistic to expect to determine the algorithms by relying only on low-level neural mechanisms. An appropriate method is to start from a theoretical viewpoint to establish the model wiring of the neural network, and to analyze its dynamic properties in order to reveal its biological meaning.

In reality, as early as more than 40 years ago researchers began to follow this appropriate method; many useful results [4] were obtained. Representative examples of this kind of early research are the threshold value element model by McCulloch and Pitts, the linear element model of Hartline, and the neural memory model of Caianiello. Recently, extensive studies were conducted on the doubled-valued and continuous nonlinear neuron model circuit when exploring the problem of associative memory. For example, as pointed out by Little [5], if the synaptic connections in a neural network are symmetric, then the system will evolve to a fixed sequential state. Professor Hopfield of the California Institute of Technology introduced the concept of energy function in his model neural network, indicating [6] that the system will be eventually in a state of minimum energy function if the synaptic connections are efficient and symmetric. Consequently, he proposed a rational framework [7] for understanding the computational properties of a neural network. One may conclude that this framework is an important result with new meaning as obtained under the guidance of Marr's theory because the framework has four following properties that are noteworthy:

(1) A category of optimal problems can be naturally projected into the neural network. Through the relationship between the system stabilized point and the dynamic process exposed by the energy function, direct understanding can be reached on how a neural network solves this kind of problem.

(2) This relationship confers an auxiliary advantage: a contrast can be made with spin glass with its large amount of data on statistical mechanics, thus introducing methods of physics and systems science into research on neuroscience.

(3) Concerning methodology, this framework has its roots in the theory of visual computation, therefore the framework can be

used to solve some problems about vision. In this sense, the framework is really a development of Marr's computational theory.

(4) In nature, the computations executed by the model neural network differ from Boolean algebraic operations, therefore the model has very great appeal to researchers on new-generation computers currently under development.

The paper presents Hopfield's work, stressing the description of collective computational properties, and explaining that his proposed rational framework is a natural method of studying neural network computation. Finally, the authors apply the model neural network in elementary vision in order to enable readers to understand and evaluate Hopfield's model with its significance.

II. Model Circuit of Neural Network

Let us consider the following bioneuron model: its input is from another neuron to its dendrite, and its output is from the axon synapse to another neuron. The action potential is generated near the cell body and is conducted along the axon to stimulate the synapse. Assume that the electrical effects as caused by dendrite shape and axon can be neglected, and only fast synaptic events are considered, then the potential variation leads to simultaneous variation of electrical conduction in cell i presynaptically when the potential variation occurs in cell j. The magnitude of electric conduction variation is determined by nature and intensity of the synapse from cell j to i.

The neuron generating action potential operates in the steady state as described above; its impulse transmission velocity is determined by input current from the synapse. By changing the cell body and cellular current, the input current plays its role indirectly. The discharge time constant is determined by cell capacitance C_i and membrance resistance R_i. By integrating time constant R_iC_i over input current, the value of the equivalent input potential u_i can be determined. Actually, u_i is the cell membrane potential after subtraction of the action potential. The action potential is the reaction of postsynaptic cell body after induction of the synapse; the reaction velocity is determined by the value of u_i, denoted by $f_i(u_i)$. The relation between conduction velocity and input current (u_i) can be described with a simple harmonic S-shaped curve. By inputting a synapse into neuron j presynaptically into neuron i that is postsynaptic, the synaptic current intensity is proportional to the product of $f_i(u_i)$ of neuron j, and the synaptic intensity T_{ij} from j to i. In other words, current of presynaptic neuron i is determined by $T_{ij} \times f_j(u_j)$; hence, the function of the action potential is described with a continuous variable.

Many neurons operate according to the graded response mode; they generally do not generate an action potential. However, the presynaptic terminal can secrete a neurotransmitter, hence capable of inducing current postsynaptically. The current generating rate is determined by the potential of the presynaptic cell. This kind of neuron equivalent output is also an S-shaped simple harmonic function inputted by the synapse. Hence, whether an action-potential-generating neuron or a hierarchical-reaction-causing neuron, their model neurons can be described by using the same mathematical form as shown in Figure 1A.

Assume that a neural network is composed of N neurons. Under the above mentioned hypothesis, the dynamic equation [6] of neural network can be obtained:

$$C_i \frac{du_i}{dt} = \sum_{j=1}^{N} T_{ij} f_j(u_j) - \frac{u_i}{R_i} + I_i, \quad i = 1,2,\cdots,N \qquad (1)$$

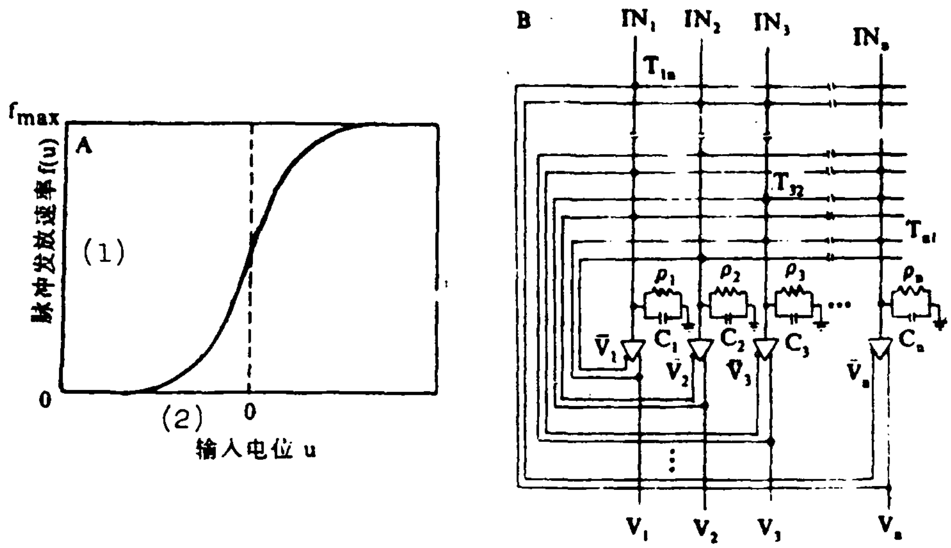

Fig. 1. Input--Output Relation (A) of Model Neuron and Electron Simulation Circuitry of Model Neural Network (quoted from [6]).

Key: 1. Impulse transmission velocity f(u);
2. Input potential u.

This nonlinear differential equation set can be considered a kind of description in classical nerve dynamics. It shows that to neuron i, the net input current of u_i for charging input capacitance C_i is composed of the three following parts: a. current behind the synapse induced in neuron i due to activity of resynaptic neuron j; b. leakage current in neuron i as flowing past the input resistance R_i; and c. input current from other neurons extrinsic to the network. For any assumed neural network defined by specific values of T_{ij}, I_i, f_i, C_i and R_i, its time evolution process can be obtained by numerical integration of equation (1).

As described in equation (1), the system dynamic process can also be simulated with an electronic circuit shown in Figure 1B. This feature is very important because electronic simulation not only can present a direct image of the dynamic process of the network, but also provide a direct image of network dynamic state in addition to providing a direct avenue for realizing the technique of network computational functioning. In this model nerve network, a neuron is a computational amplifier with a feedback circuit that is made up of resistance, capacitance and connecting wires, capable of connecting axon, dendrite and synapse. Like equation (1), the input current of any amplifier is composed of three parts: current, leakage current and extrinsically inputted presynaptic current. Table 1 shows the parametric corresponding relation between the electronic and the model neurons.

In the model expressed in equation (1) and Figure 1, considerable simplfication was made on the properties of bioneurons but the following features of the biological system are stressed because they are important to the system:

1. For the neuron as an input-output conversion apparatus, its transmission property is an S-shaped smooth curve from 0 to the maximum output.

2. The cell membrane has a function of time space summation.

3. There are large numbers of excitatory and inhibitory connections among neurons; these kinds of connections are realized mainly through feedback.

4. By representing the immediate generation of the action potential, the neuron also represents the ability of operating in the graded response mode.

Therefore, what the model neuron precisely retains is the two most important computational (dynamic and nonlinear) features. Undoubtedly, this is an appropriate model for theoretical research aimed at explaining how to generate the intensive computational capability by coordinated functioning among neurons.

Table 1. Corresponding Relationship Between Amplifier and Model Neuron Parameter.

参数名称 (1)	模型神经元 (2)	放大器 (3)
输入(神经元的膜电位)(4)	u_i	u_i
输出(动作电位的发放速率或引起突触后电流的速率)(5)	$f_i(u_i)$	$V_i=(V_i^{max})\rho_i(u_i)$
突触联结强度 (6)	T_{ij}	R_{ij}
输入阻抗 (7)	$R_i // C_i$	$\rho_i // C_i$
漏电流 (8)	u_i/R_i	u_i/R_i,这里 (10) $\frac{1}{R_i}=\frac{1}{\rho_i}+\sum_j\frac{1}{R_{ij}}$
外部输入电流 (9)	I_i	(11) 由联线 *IN* 提供

Key:
1. Name of parameter;
2. Model neuron;
3. Amplifier;
4. Membrane potential of input neuron;
5. Output (transmission velocity of action potential or current velocity after causing synapse);
6. Connection strength of synapse;
7. Input impedance;
8. Leakage current;
9. Extrinsically input current;
10. Here;
11. Provided by connection line IN.

V_i is the output potential of the amplifier; V_i^{max} is the proportionality factor; $\rho_i(u_i)$ is dimensionless function with the same shape as that of $f_i(u_i)$. The maximum output values of the amplifier is 1; V_i is the corresponding maximum transmission velocity of neuron i; $1/(R_{ij})=1/(\text{absolute value of } T_{ij})$ is the feedback resistance of the amplifier; by connecting with the plus phase amplifier, R_{ij} denotes an excitatory synapse (for the case of linking with the reverse-direction amplifier, R_{ij} denotes an inhibitory synapse); and IN connects with a direct current supply extrinsic to the network.

III. Rational Framework for Understanding Dynamic Features of Neural Network

As expressed in equation set (1) and Figure 1, the features of the neural network is determined by synaptic connection strength T_{ij} and extrinsically input current I_i. For a given T_{ij} and I_i, the system state can be described with output value V_i of various neurons in the network. Assume that V_i corresponds to a coordinate axis in N-dimensional Cartesian coordinate system, then the system's instantaneous state can be expressed with an N-dimensional vector that is a point in N-dimensional space; hence, the dynamic process of the network is the movement of this point in the state space. The computational result of the network is the steady state of movement.

Assume that the system has several locally steady limiting points X_a, X_b, ..., then the computational result is certainly $X \gtrsim X_a$ when the system is sufficiently close to the position of X_a at the start of processing of $X=X_a+\Delta$. In this state, we can consider the information stored in the system as vectors X_a, X_b, ... If the beginning position $X=X_a+\Delta$ is one part of the information of X_a, then the system will spontaneously release complete information of the generating X_a. This system that is capable of producing complete information is called a memory with data addressing, generally also called an associative memory device. Obviously, the nature of associative memory processing is that the system's dynamic process should be convergent to a set of locally steady points; the other kind of processing executed by the neural system is also important, as we will see.

From the viewpoint of mechanics, a locally steady point corresponds to a state in which the system energy is at a locally minimum state. Hence, the neural network can at least be defined mathematically as a computational energy function, the Liapunov function. Through the function, the collective computation feature of describing a neural network can be described. For example, the associative memory network can be defined as energy function (6).

$$E = -\frac{1}{2}\sum_i\sum_j T_{ij}V_iV_j + \sum_i \frac{1}{R_i}\int_0^{V_i} g_i^{-1}(V)dV + \sum_i I_iV_i \tag{2}$$

In the equation, $g_i^{-i}(V_i)=u_i$, indicating the input-output relation of a neuron. Assume that T_{ij} is effectively symmetrical (functioning through interneurons); in the deriving time derivative from equation (2), we obtain

$$\frac{dE}{dt} = -\sum_i \frac{dV_i}{dt}\left(\sum_j T_{ij}V_j - \frac{u_i}{R_i} + I_i\right) \tag{3}$$

Substitute equation (1) into the above equation, then we have

$$\begin{aligned}\frac{dE}{dt} &= -\sum_i C_i\left(\frac{dV_i}{dt}\right)\left(\frac{du_i}{dt}\right)\\ &= -\sum_i C_i\frac{d}{dV_i}g_i^{-1}(V_i)\left(\frac{dV_i}{dt}\right)^2\end{aligned} \tag{4}$$

Since $g_i^{-1}(V_i)$ is a simple harmonic increasing function, C_i is a positive number; hence, no negative values can be obtained in various summation items in equation (4). Then we have

$$\frac{dE}{dt} \leq 0, \quad \frac{dE}{dt} = 0 \rightarrow \frac{dV_i}{dt} = 0, \qquad \forall i \tag{5}$$

An energy function always has limit; therefore, equation (5) indicates that the system in state space can enable the total movement energy find the position of the minimum value for energy function E, and stays at these positions.

Figure 2 shows the system's energy terrain diagram composed of two neurons corresponding to two steady points with very small energy within a square prescribed by two steady points with very small energy inside a square. However, when the amplifier has very high gain so that the integrating item in equation (2) approaches zero, then the system's steady point will be composed of the locally very small value of energy function

$$E=\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}T_{ij}V_iV_j-\sum_{i=1}^{N}V_iI_i \tag{2}$$

The steady points are located at 2^N vertex angles of an N-dimensional hypercube. At that time, the steady points of the continuous value model network will directly correspond to steady points of the two-valued model network [8-9].

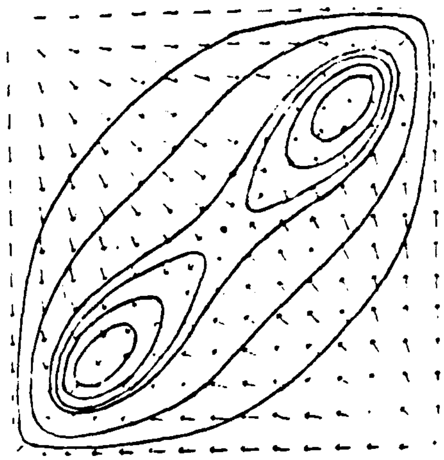

Fig. 2. Energy Contour Terrain Diagram of Double Steady State Model Neural Network (arrowheads in the diagram indicate motion direction (cited from [6])).

Hence, whether a continuous-value model or a divergent-value model, all energy functions can indicate the internal connection between the system steady point and dynamic process. Based on this relation, we can compose an associative memory network [6, 7]. Actually, only by considering that the associative momory problem as an optimal problem, can it be related to the solution of the neural network through the energy function; thus, the problem of how the neural network solves the associative memory problem can be directly understood. In other words, when placing the steady state of the system on a set of special memory states, this purpose can be achieved only by selecting the appropriate parameters T_{ij} and I_i so that the network is in a situation in which the energy function of the memory state is locally minimum. For example, for a set of a total of m memory states V^6,S=1,2,...,m select the energy function

$$E = -\frac{1}{2}\sum_{s=1}^{m}(V^s \cdot V)^2$$ then we can derive $T_{ij} = \sum_{s=1}^{m} V_i^s V_j^s$ and $I_i=0$

As mentioned above, the method for understanding the associative memory network is of general significance. This method can be used to solve many problems, such as analog to digital conversion, decomposition/decision of signals, linear planning [10], and the salesman's travel route [7]. In certain conditions, the optimization problem can be naturally connected with computations executed by the neural network through the energy function. For a system of symmetry in synaptic intensity, we have the following theorem: in a symmetric network, if the input-output relation of a model neuron is simple harmonically limited, and the variation is very slow for the input current (if it exists) extrinsic to the network during the network computation process, then the energy function is always attenuated with time in the dynamic process of neural network as described in equation (1). In other words, beginning from any initial state, the system will move along the descending direction of energy function. After arriving at the local minimum, the system stops moving. However, if the synaptic intensity is not symmetric, there is no unified movement criterion in the system. The system's attractor can possibly be the steady point and also possibly be the limit ring, and even fuzziness phenomena may appear.

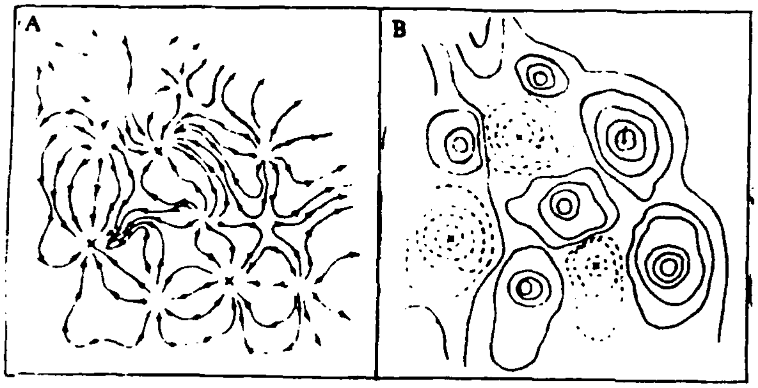

Fig. 3. Dynamic Process (A) and Energy Terrain Diagram (B) of Symmetric Network.

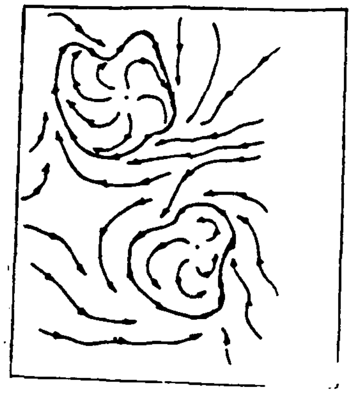

Fig. 4. Limit Ring Abstractor Possibly Appearing in Unsymmetric Neural Network.

The above-mentioned concept can be explained with the phase space diagram. Figure 3 shows the two-dimensional phase plane diagram. Every curve in A corresponds to a movement possibly occurring in the system; arrowheads indicate the directions of movement. Every movement locus approaches a steady point and stops there. B is the energy terrain diagram of A. Figure 4 is an example of the possible appearance of limit rings in an unsymmetric network.

The energy function is the overall quantity of the system; every neuron cannot be in a condition of awareness. The state of various neurons is determined by the neuron's equation of movement (1). Through the energy function, we can naturally project a specific computation problem onto the neural network with symmetric connections. Thus we can directly understand the fashion of solving problems in a model neural network. As general methodology, the energy function also provides an important means for neurophysiologists to understand the computational features of the bioneural network. Obviously, the energy function is like the concept of entropy in statistical mechanics.

IV. The Problem of Solving Difficulties by Using Model Neural Network

We know how to solve problems of associative memory in a model neural network by using the energy function. However, the associative memory problem is only a simple optimization problem. With respect to complex problems such as a salesman's travel route (called as the TSP problem in the following), how can the situation be handled?

The TSP problem is a notably difficult problem that has been studied intensively. The problem is quite clearcut: it is required that a salesman covers n cities according to a certain sequence. In his itinerary, he only visits every city once, and finally he returns to his starting point. In the question, he is to select the shortest closed route among many possible routes. Here, the total length of a route is determined by distances between paired cities. This is a so-called combinatorial explosion problem; the computational volume will rapidly increase with increasing n. When n is a very large number, solving this problem with present-day computers is difficult. However, the above-mentioned difficulty is easy to overcome by using the neural network. Like the associative memory problem, the TSP problem can be solved through the three following steps [7].

4.1 Mode of formulating the TSP problem

The solution of a TSP problem with n cities is a sequential table composed of n cities. Assume that the final positions of n cities are determined by the output status of n neurons. Then it is required that in the problem of n cities, there should be $N=n^2$ neurons to express a complete route. For convenience, the output of n^2 neurons is arranged in a matrix. For the problem of five cities, one state of network neurons is as follows:

	1	2	3	4	5
A	0	1	0	0	0
B	0	0	0	1	0
C	1	0	0	0	0
D	0	0	0	0	1
E	0	0	1	0	0

(6)

Equation (6) is called a transfer matrix, which indicates a route such as the follows: a salesman begins his journey at city C; his first destination is city A, ... Finally, the salesman returns to city C. Obviously, in an effective route-indicating solution, the position occupied by any city cannot be more than one; a position can be only occupied by a single city. In other words, in describing the output state of an effective route, there can only be one "1" output in a row, or a column; all the others are "0." For decoding any transfer matrix composed of output values, a route (the one solution of the problem) can be obtained. It is not difficult to understand that there are a total of n!/2n closed routes for a TSP problem of n cities.

4.2 Energy function of TSP problem

The energy function of describing a TSP problem should satisfy the two following requirements:

(1) The energy function should facilitate reaching the most stable state for the transfer matrix expressed by

equation (6); and

(2) The energy function should facilitate expression of the shortest distance route in n!/2n solutions.

Considering requirement (1), the following energy function can be selected:

$$E_1 = \frac{A}{2}\sum_x \sum_i \sum_{j\neq i} V_{xi}V_{xj} + \frac{B}{2}\sum_i \sum_x \sum_{y\neq x} V_{xi}V_{yi} + \frac{C}{2}\left(\sum_x \sum_i V_{xi} - n\right)^2 \qquad (7)$$

Considering requirement (2), the following energy function can be selected:

$$E_2 = \frac{1}{2D}\sum_x \sum_{y\neq x} \sum_i d_{xy} V_{xi}\left(V_{y,i+1} + V_{y,i-1}\right) \qquad (8)$$

Numerically, in equation (8) E_2 is equal to the length of several lines. In equations (7) and (8), the outputs of the neurons are expressed with dual footnotes. The row footnotes are the names of cities while column footnotes are the positions of these cities. To express the final effect of several closed lines, the modulus of footnotes is n.

The overall energy function is the summation of equations (7) and (8). If ABC is a large enough number, all low energy states are forms of expressing effective routes for the network described with the energy function. However, the state with the shortest route is the state in which the energy is at the lowest.

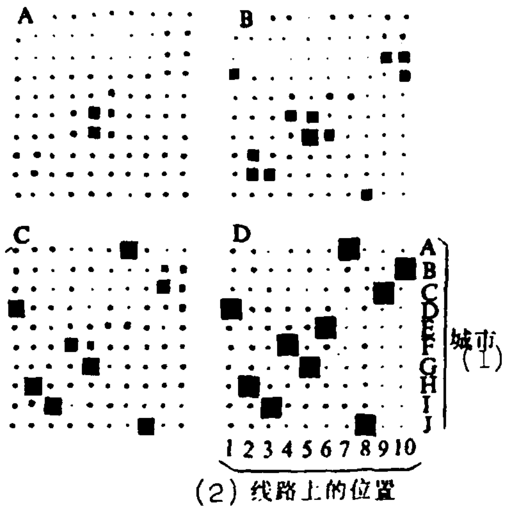

Fig. 5. Convergent Process of Model Neural Network for Solving a TSP Problem With 10 Cities (quote [7]).

Key: (1) City;
(2) Positions at route.

4.3 Composing a model neural network

Based on equations (7) and (8), the joint matrix T_{ij} can be determined by secondary terms involving the energy function; however, the extrinsic input current I_i is determined by the linear terms. By the dual footnotes method as mentioned above, we can obtain the joint matrix defined by the implicit function as follows:

$T_{xi,yj} = -A(1-\delta_{ij})\delta_{xy}$ limiting connection with each row
$-B(1-\delta_{xy})\delta_{ij}$ limiting connection within each column
$-C$ integrated limiting function
$-d_{xy}(\delta_{j,i+1}+\delta_{j,i-1})$ data term

$$[\delta_{ij}=\begin{cases}1, i=j\\0, \text{ other situations}\end{cases}] \qquad (9)$$

The externally inputting current is

$$I_{xi}=+C_n \quad \text{stimulation offset} \qquad (10)$$

In T_{ij}, the data term for the system as D is a kind of input; this explains which TSP problem should be solved. However, as required by any TSP problem, a general constraint is provided for those terms with coefficients as A, B and C. Since the energy function controls the dynamic process of the network, the final state like that in equation (6) can be derived after beginning with the initial offset of the network. In other words, the network can select the optimal circuit among $n!/2n$ final states satisfying the constraint conditions under the function of data terms.

Figure 5 shows the computer simulation result of a TSP problem with 10 cities. The network never inclines toward any special circuit of its state with a noise function for beginning its operation. After a very short time period (approximately several time constants for states a, b and c), the network is convergent at state a. For the problem of 10 cities, there are a total of $10!/20$ (approximately 2×10^5) circuits. From this many circuits, the network selects the *two shortest* circuits. Therefore, the selectivity coefficient of this sort of network is $2/(2 \times 10^5) = 10^{-5}$.

For a TSP problem with 30 cities, the total number of circuits is approximately 10^{30}. Therefore this is a difficult (to control) problem. However, in a one-time convergence (approximately several time constants), the network composed of 30x30 neurons can select 10^7 good solutions in expelling bad solutions numbering 10^{23} times (good solutions). The selectivity coefficient is 10^{-23}.

Thus, it can be seen what a good approach in solving the TSP problem we have been examining. We have reason to believe that this unusually rapid and effective computation capability is a natural result of utilizing the continuous variant and feedback loop. System 0-1 does not have this sort of capability. Hence, the computation executed by model neural network is concretely different from the Bohr logic operation.

V. Application of Model Neural Network in Initial Stage Vision

As described above, the Hopfield model has been developed under guidance of the theory of computer vision; therefore, the model naturally can solve problems in vision research. For example, we can apply the model to solve the surface interpolation problem [11] capable of maintaining noncontinuity.

There are two methods of reestablishing the surface from data measurement: one is the reestablishment of a smooth surface, capable of being solving with the standard regularization theory [12]. Another method is the reestablishment of a smooth surface section by section; this is a problem of nonsecondary type, capable of being solved with random regularization method [13]. The model of reestablishment of a smooth surface section by section is composed of two mutually coupling Markov random field: one is the field of taking continuous values; the depth value is f_i as measured corresponding to position i. Another is the field of taking secondary values; its variant is between lattice points of depth measurement. In this implicit function of linear treatment, whether noncontinuity exists between two adjacent depth elements is to be pointed out. Under the Bayesian estimate corresponding to an energy function, the overall property of the maximum estimate of the surface is very small.

As pointed out in the Hopfield model, the relationship in state variants between the continuous-valued model and binary-valued model is determined by the gain of the amplifier. When $\lambda \to \infty$, the amplifier output is 0 or 1. Hence, the linear treatment of the two values can be projected in continuous variant limited by 0 or 1. By only selecting the appropriate energy function and renewal rule, it can be proven that the total energy of the network is always attenuated with time. The system will evolve in attenuation fashion, and finally a minimum value of E is attained. To a diagram composed of 32x32 image elements, the result of computer simulation is shown as in Figure 6. The left upper corner in the figure shows the initial state of the network; the right lower corner shows the final state. Thus, it is effective by using the Hopfield model in reestablishment of the smooth surface section by section.

Figure 7A is a simulation network of carrying out surface smooth interpolation section by section. The basic concept is to combine a programmable parallel-processing device with local connection, and a linear network composed of electric resistance in a hybrid device. Corresponding to the linear element, a digital processor can cut off the resistance connection between two adjacent simulation processors by using simple switches. This kind of hybrid device has two periods of fundamental operations. Within the period of simulation operation, the processor leads the current (corresponding to depth measurement) into a simulation network. Then under the given linear distributed situation, the resistance network finds out the (only) surface as the smoothest. Within the period of digital operation, the digital processing network reads out the current values of resistance at various nodal points in the resistance network. In addition, by using the software of a compiled program, recomputation is conducted with linear processing of the two values. Here, the random optimization method is easily carried out. Then the processing will appropriately break off connection lines in the simulation network. In designing an artificial vision system, this configuration of the computation network is a new concept. Figure 7B shows an imaginary mechanism of the neural network of the hybrid device.

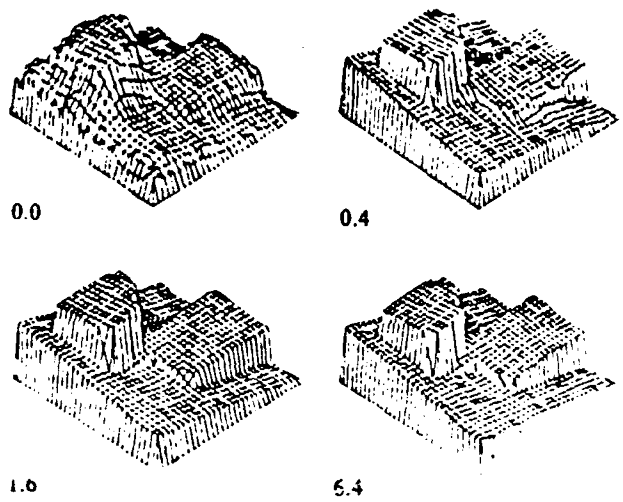

Fig. 6. Processing Procedure of Neural Network (quoted from [11]) for Interpolation of Field Scene Composed of Three Inclined Cuboids.

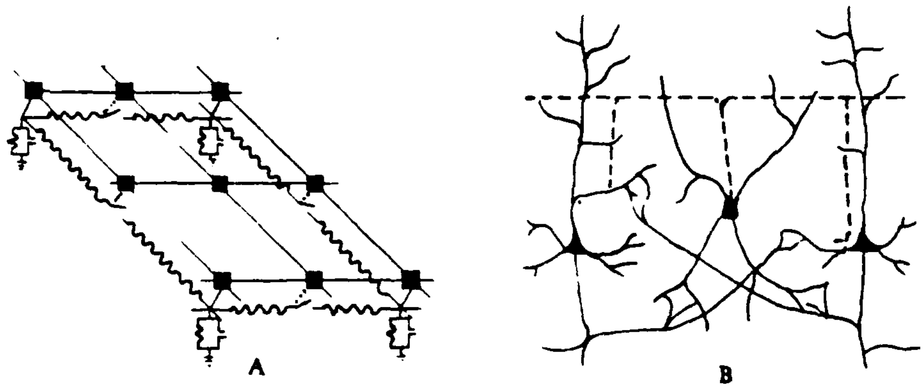

Fig. 7. Mixed Type Circuit (A) and Its Nerve Realization (quoted from [11]) in Carrying out Smooth Surface Interpolation Section by Section.

VI. Discussion

After we have described the general situation of neural network research and the rational framework of collective computation of neural network, the following conclusions can be reached:

(1) Computer vision reveals the prologue of computational neuroscience. Computer vision can be regarded as a genuinely borderland discipline; with its lead, computer science, mathematics, physics, systems science and systems engineering (in addition to the traditional neuroscience method) are included in the realm of neuroscience, which begins to show its brightness. This method of utilizing interdisciplinary research is an important source of creative concepts. Undoubtedly, this approach will considerably speed up neuroscience research in markedly changing the achievements of neuroscience. Recently, a Department of Brain and Recognition Science was established at the Massachusettts Institute of Technology, and again recently a Research Project of Computation and Neural Systems was proposed by the California Institute of Technology. These are important decision steps taken with this kind of recognition. Hence, we have reason to believe that computational neuroscience has become a major research direction in neuroscience.

(2) In the rational framework of Hopfield's collective computation of a neural network, a category of the optimal problems can be naturally projected into a neural network with symmetric connections. In particular, with the introduction of the energy function and the application of design circuitry, we can understand how the optimal solution can be derived by a model neural network, which realizes the features of analog and digital computers. However, essentially the model neural network is different from either of these computers. On the one hand, the network integrates data expression and programming of digital computation. On the other, the network uses analog computation to replace Boolean logic operation. Here, the differential equation of the model is not of concrete significance; essentially, the differential equation is a program; through it, a solution of the problem can be obtained. This sort of collective computation property of the model neural network is obviously very significant to research on new-generation

computers under development or present-day intelligent computer. Actually, Hopfield's work attracted the general attention of researchers. Not only are there high challenges at the level of theoretical research, but the corresponding chips were also manufactured. For example, chips for solving movement computing problems have been manufactured in the United States. Therefore, we should stress this new trend of neuroscience research.

(3) At the same time, we must realize that the present results have considerable limitations because research in computational neuroscience is in its infancy. Many problems are waiting for solution by researchers.

For example, network parameters are given in Hopfield's theoretical framework. In other words, his proposed parameters of a model neural network are written into the network after man have advanced in computer science. The network by itself does not have properties of learning and adaptation. Hence, it should be clarified how a neural network with certain functions can be self-organized [14] through learning and adaptation in order to achieve the unity of human intelligent behavior and neural structure; there is a relatively long distance to be covered. For another example, Hopfield's model demands that the connections of a neural network should be symmetric. This point, however, is not established in all situations. Actually, some networks are not symmetrical. One of the dynamic features of unsymmetrical network is the existence of limit ring attractor, whose concrete computational approach and meaning are not understood by researchers, not to mention fuzziness phenomena. For this kind of theoretical problems, it is possibly required to have even higher theoretical viewpoints for research treatment.

On this aspect, some help to research can be provided by Prigogine's theory on dissipation structure, Haken's coordination theory theory, and Thom's mutation theory. It can be believed that once theories like dissipation structure are established in neuroscience, this will a new face in a revolutionary change.

The focus of actually applying Hopfield's model is concentrated at present on processing problems of associative memory and initial stage vision. According to Hopfield's estimate [8], the model's memory capacity is only N=0.15n. However, if signals are appropriately encoded in advance, memory capacity can be greatly increased. Hence, during research on problems of associative memory, research on programming technology should be opportunely developed. Hopfield's model has some use in initial-stage vision as the model can solve problems [11] that cannot be solved by the standard regularization theory. However, when the energy function is of non-secondary type, at present it cannot ensure that the network can process to the state in which energy is at the minimum. Development and perfection of this aspect of work is also a problem concerning by researchers.

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