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Evolving Cellular Automata Neural Systems (ECANS 1)

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Abstract

This paper is our first attempt to construct a information processing system such as the living creatures' brain based on artificial life technique. In this paper, we propose a method of constructing neural networks using bio-inspired emergent and evolutionary concept. Ontogeny of living things is realized by cellular automata model and Phylogeny that is living things adaptation ability themselves to given environment, are realized by evolutionary algorithms. Proposing evolving cellular automata neural systems are called in a word ECANS. A basic component of ECANS is 'cell' which is modeled on chaotic neuron with complex characteristics. In our system, the states of cell are classified into eight by method of connecting neighborhood cells. When a problem is given, ECANS adapt itself to the problem by evolutionary method. For fixed cells transition rule, the structure of neural network is adapted by change of initial cell's arrangement. This initial cell is to become a network by developmental process. The effectiveness and the capability of proposed scheme are verified by applying it to pattern classification and robot control problem.

Keywords : artificial life, neural networks, cellular automata, evolutionary algorithms, chaotic neuron

1. Introduction

In recent years, artificial life concept becomes one of the most popular researches as a solution of intelligent information processing system under uncertain, complex and dynamic environments. The purpose of artificial life researches is to understand the nature of living things and to construct the system that is similar to life in a artificial media. Representative models of artificial life are cellular automata(CA), L-system, neural networks(NNs), fuzzy system(FS), genetic algorithms(GAs) and swarm intelligence(SI) etc.. Specially, neural networks and genetic algorithms are very popular and important model of artificial life[1].

The success of neural networks in information processing tasks depends mostly on well-designed structures of the systems. Structures have to be defined before learning algorithms are applied. Although, in practice, determination of structures takes most of effort in adjusting a neural system to particular tasks. There are still no effective rule or systematical approaches to determine structure in neural systems. Thus, evolutionary approach is introduced for the structure and the parameter optimization in recent researches. Several constructing methods of neural network have been proposed to date. L-system based modular artificial neural network[2] and CA-based brain system (CAM-Brain)[3] are developed. But this method is still in developing step.

In this paper we propose a new type of neural networks that is based on cellular automata and genetic algorithms. we call this evolving cellular automata neural systems(ECANS). In the living creatures of nature, a reproductive cell segments and grows according to the genetic information, and it becomes a multicellular organism. And also this organism is adapted the given environment through evolutionary process. Like this, the proposed neural networks model is composed of two different model; one is developmental model(cellular automata) and the other is evolutionary model(genetic algorithms).

The brain of living creatures is developed by genetic information in fetus. And at the same time, the instinct behavior is also programed. Therefore instinct behavior is not learned but native. Conventional neural networks are able to solve the problem by learning, so up to now, this native instinct behavior has not been realized in artificial neural networks. In our system, in order to make native instinct behavior ability, we assume that there is no weight among neurons, but only connection. Therefore, learning process need not performed. So each type of cell (neuron) and its arrangement are important to construct neural networks. According to the arrangement of these various cells, the characteristics of the neural networks is determined.

Usually, evolutionary algorithms are considered more efficient for optimal system design because evolutionary algorithms can provides higher opportunity for obtaining the global optimal solution. Recent years, evolutionary algorithms are applied to neural network learning and structure searching. By evolutionary computation, a parameter of neural network is optimized for the given environment.

4.2 Ability of CANS

Cellular Automata Neural Systems(CANS) that we propose, is only a network framework. For the purpose of applying a given problem, it is necessary to make a network to optimal structure.

Animal has innate instinct behavior when they was born. This instinct has been succeeded and improved by generation to generation. Like this, cellular automata neural system has optimal structure for given tasks by evolutionary algorithms. In order to applying CANS to evolutionary algorithms, initial cell of the system is encoded into chromosome. Throughout the generation, each individual(initial cells) go through process of ontogeny, and result network is evaluated in given environment.

5. Simulation Result of Some Problems

5.1 Pattern classification problem

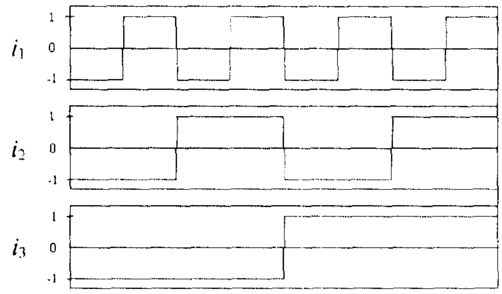
We apply ECANS to the XOR and 3 bit parity problem, in order to verify the ability of pattern classification of which is not classified linearly.

The parameters used in 3 bit parity problem are as follows.

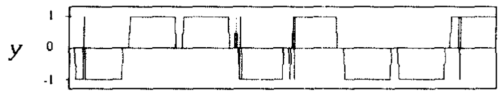
$k_e^d, k_f^d, k_r^d = 0.5, \ \theta_i = 0, \ \alpha = 1, \ \varepsilon = 0.015$
\# of input : 3
\# of output : 1
\# of initial cells : 3 × 3(input) = 9 cells
\# of states : 8 states
development level : 5 steps
Rule: $\Phi_i(\sigma_i) = (\sigma_{i-1} + \sigma_i + \sigma_{i+r})\%$ *# of total states*

Fig 6 (a) is patterns of 3 inputs and (b) is pattern of output that is result of 100 generation evolve. Finally obtained network's structure is shown in Fig. 7, and a change of fitness is in Fig. 8.

As a result of experiments of different conditions, the proper number of initial cells is 3 times of inputs and a level of development is 5 to 10. Too small number of development level is not good for result. And when we use large number of development level, the effect of input signal to output is dim. So, in this experiment, the level of development is adopted as 5. This result is similar to the cerebral cortex of animal which is consist of 5 to 10 layer neurons.



(a) Input



(b) Output

Fig. 6 Response of 3-parity problem

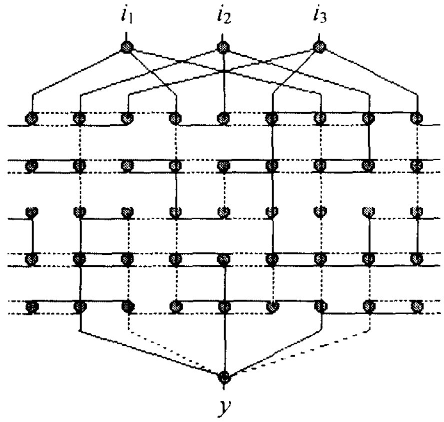


Fig. 7 Obtained network(100 generation evolution)

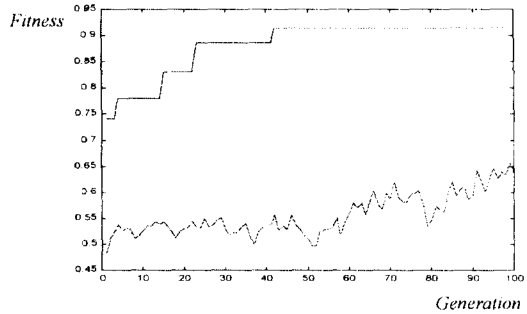


Fig. 8 A change of fitness
(upper : best fitness, lower : mean fitness)

5.2 Robot navigation and path planning

For the purpose of knowing not only classification ability but also nonlinear mapping and memorial ability of ECANS, we apply it to the navigation problem of autonomous mobile robot. A environment for application is a regular square area. one corner of it is starting point and other point is final goal. Obstacles are put in between start point and goal. Objective of this system is for robot to go to goal without collision. The inputs of the robot are 3 directional sensor values and a angle between forward and the direction of goal. The outputs are force of 2 wheels. At this time, output neuron of

$$c_i(t+1) = -\alpha \sum_{d=0}^{L} k_r^d x_i(t-d) - \theta_i \tag{10}$$

Rearrangement of this equations yields equation (11) to (13).

$$a_i(t+1) = k_e a_i(t) + \sum_{j=0}^{M} v_{ij} A_j(t) \tag{11}$$

$$b_i(t+1) = k_f b_i(t) + \sum_{j=0}^{N} w_{ij} x_j(t) \tag{12}$$

$$c_i(t+1) = k_r c_i(t) - \alpha x_i(t) - \theta_i(1-k_r) \tag{13}$$

Because equation (11) to (13) are represented as discrete equation; so additional memory for simulation and implementation is not needed.

3.3.2 Chaotic dynamics of chaotic neuron

In this section, we will show the characteristics of cellular automata neural networks. One neuron of networks has chaotic dynamics(Fig. 4 (a)). And some connection of neuron also shows chaotic behavior. Fig 3 shows a simple network and, Fig 4. shows chaotic behavior of x_1 to x_4 of network in Fig 3. This is bifercation diagram of parameter i(input). CANS has not weight but only has excitation synapse, inhibitory synapse and no connection. So complexity of network itself is very simple. However network shows very complex behavior, because of chaotic dynamics of a neuron.

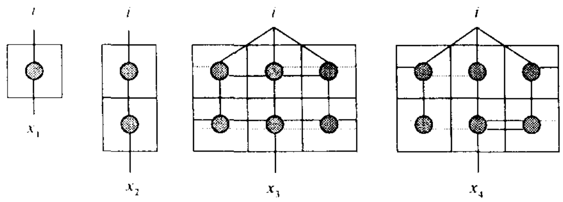
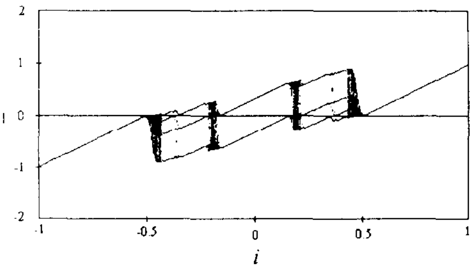
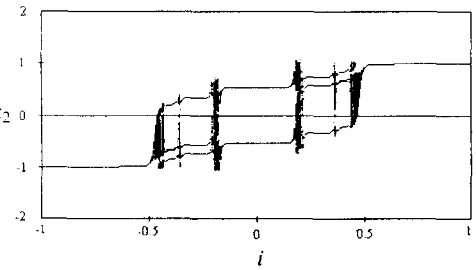


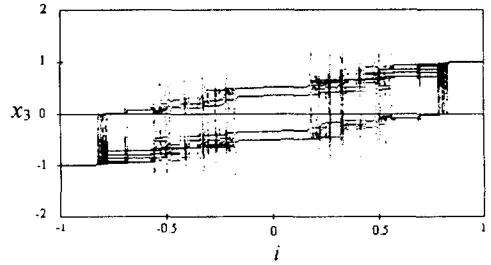
Fig. 3 Examples of a simple network



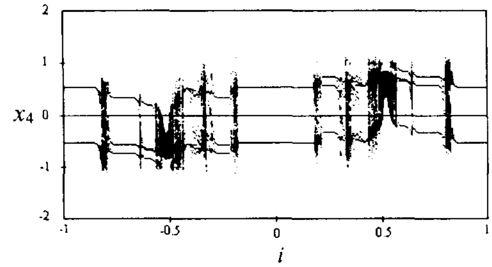
(a) state of x_1



(b) state of x_2



(c) state of x_3



(d) state of x_4

Fig. 4 Bifercation Diagram of input i vs state x of which network in Fig 3.

3.4 Cellular automata neural networks

In order to construct the neural network, Initial cells must go through the developmental process of cellular automata. But how much level to develop the cells, and how many initial cells to be needed is not defined. As a result of several experiments, it is proper that a number of initial cells is 3 times of inputs and a level of development is 5 to 10. But this is only result of some experience, a reasonable method to obtain the parameter is object of the future work(see section 6).

Fig. 5 shows the developmental process and how to connect the input and output cells to the network.

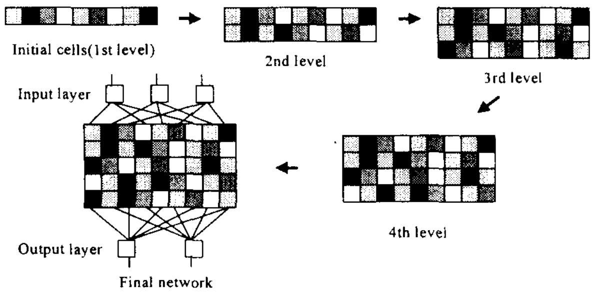


Fig. 5 Developmental level of CANS

4. Evolutionary learning of CANS

4.1 Concept of Evolutionary Learning

The Evolution by natural selection is a central idea in biology, and the concept of natural selection has influenced our view of biological systems tremendously. Evolutionary algorithms are computational models of evolution that play a important role in many artificial life models[9].

$$\phi : \Sigma^{2r+1} \rightarrow \Sigma \tag{2}$$

The all-important property of cellular automata, is that this function is determined by a finite look-up table. Both the domain and range of ϕ are finite.

The global function Φ arises from ϕ by defining:

$$\sigma_i^{new} = \Phi_i(\sigma_i) = \phi(\sigma_{i-r}, \cdots, \sigma_{i+r}) \tag{3}$$

A concrete example with $k = 2$, $r = 1$ would take a doubly infinite string of zeroes and ones to a new string at which each site is replaced by the logical and of its two neighbors.

3.2 Cell types

In proposed system, the states of cell is defined by relation of connecting neighborhood cells. Basic method of connection is only connect its neighbor cells. And a connection is one of which no connection(0), excitatory connection(1), and inhibitory connection(-1). Each cell is able to connect its neighborhood and the next state of self transition. Therefore total connection way is 3^3. In cellular automata, using much state affects the complexity of system. In our case, 8 of 27 states are used, considering symmetry of networks. Fig. 2 shows the selected cell's states of our system.

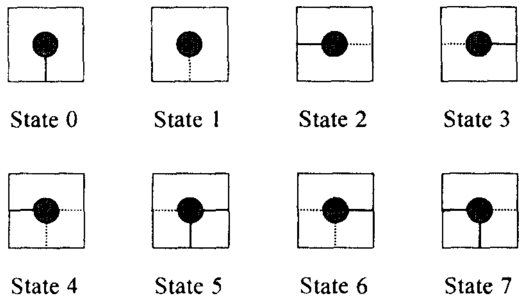


Fig 2. Selected states of cells(cell's connection type)
(dotted line : inhibitory synapse
solid line : excitatory synapse)

3.3 Chaotic neuron model

3.3.1 Chaotic neuron model

A try of research of biological information processing model of brain-nerve system was started for McCulloch-Pitts 2 valued neuron model, and extended to analog model, and modified and developed for considering input-output relation etc.. Because this model is very simple, it is compatible for analysis and simulation. However, one neuron has only simple behavior.

A neuron of ECANS is used Nagumo-Sato's chaotic neuron model[4~6] that is based on Hodgkin-Huxley equation which is deep consideration model of practical neuron membrane's characteristics. Thus, it has complex characteristics, nevertheless it has simple structure comparatively. This neuron model has dynamic characteristic. However, because the structure of neural network was static, and learning method was based on Hofield's learning law, it is applied only TSP problem or pattern recognition. In this paper, a cell of ECANS is modeled by chaotic neuron with complex dynamics and structure go through the developmental process according to CA rule.

Modified equations of Nagumo-Sato's chaotic neuron model are as follows.

$$y(t+1) = u(x(t+1)) \tag{4}$$

$$x(t+1) = S(t) - \alpha \sum_{d=0}^{t} k^d y(t-d) - \theta \tag{5}$$

where $y(t)$ is output at time t, $x(t)$ is inertia state at time t, $S(t)$ is input at time t, $u(\ )$ is unit step function, k^d is damping factor of refractoriness having values between 0 and 1. the constant α is positive parameter, and θ is threshold of neuron.

Eq. (4) and (5) is converted to network equation by adding input term from other neuron. Output and state of i-th neuron is as follows.

$$y_i(t+1) = f(x_i(t+1)) \tag{6}$$

$$x_i(t+1) = \sum_{j=1}^{N} v_{ij} \sum_{d=0}^{t} k_e^d I_j(t-d) + \sum_{j=1}^{M} w_{ij} \sum_{d=0}^{t} k_f^d y_i(t-d) - \alpha \sum_{d=0}^{t} k_r^d y(t-d) - \theta_i \tag{7}$$

w_{ij} : weight value between j-th neuron and i-th neuron in current layer.

v_{ij} : weight value between j-th neuron in current layer and i-th neuron in upper layer

k_e^d, k_f^d, k_r^d are real values between 0 and 1, each of these values is represented the damping factor of external input term, feedback input term, and self-feedback term

θ_i : threshold of i-th neuron

$$f(x) = \frac{1}{1 + \exp(\frac{-x}{\varepsilon})}$$

The right term of equation (7) was divided into equation (8) to (10).

$$a_i(t+1) = \sum_{j=1}^{M} v_{ij} \sum_{d=0}^{t} k_e^d A_j(t-d) \tag{8}$$

$$b_i(t+1) = \sum_{j=1}^{N} w_{ij} \sum_{d=0}^{t} k_f^d x_j(t-d) \tag{9}$$

In order to obtain effective neural network structure, the initial cell of cellular automata is evolved by genetic algorithms.

In the process of cellular automata, each cell is corresponding to a neuron and the states of cell is corresponding to various types of neuron. And cell's state is determined by neighborhood cell's state. Each type of neuron has self-feedback and connection of neighborhood cells. For more complex mapping and characteristic, each neuron is modeled by chaotic neuron that is proposed by Nagumo-Sato[4~6].

In order to show the validity of the proposed neural networks model, we apply the proposed system to pattern classification problem and control of autonomous mobile robots.

2. Overview of ECANS

ECANS is based on the development and the evolution, in other words, it is modeled on the ontogeny and phylogeny of natural living things. Phylogeny concerns the temporal evolution of the genetic program, the hallmark of which is the evolution of species. The phylogenetic mechanisms are fundamentally nondeterministic, with the mutation and recombination rate providing a major source of diversity. This diversity is indispensable for the survival of living species, for their continuous adaptation to changing environment. Ontogeny is the developmental process of a multicellular organism. This process is essentially deterministic and local physics. 'Deterministic' means that once a local physics and initial state have been chosen, its future development is uniquely determined. 'Local' means that the state of a cell is a function of its own state and the state of its neighbors.

Fig. 1 shows the concept of proposed system. ECANs has two level of process that is ontogeny and phylogeny. A network is developed from initial cells, and evaluated in given environment. And genetic algorithms take a part in adaptation process.

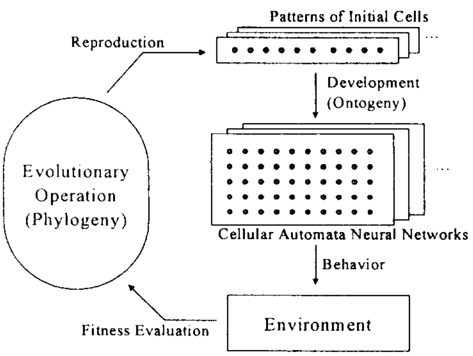


Fig. 1 Concept of ECANS

3. Cellular Automata Neural Systems

3.1 Cellular automata

A cellular automaton[7,8] is a discrete dynamical system. Space, time, and the states of the system are discrete. Space in CA is partitioned into discrete volume elements called "cells" and time progresses in discrete steps. Each cell of space is in one of a finite number of states at any one time. The states of the cells in the lattice are updated according to a local rule. That is, the state of a cell at a given time depends only on its own state one time step previously, and the states of its nearby neighbors at the previous time step. All cells on the lattice are updated synchronously. Thus the state of the entire lattice advances in discrete time steps.

The local physics is determined (typically) by an explicit mapping from all possible local states of a predefined neighborhood template (e.g., the cells bordering on a cell), to the state of one of those cells at the next time-step. For example, for a 2-state, 1D CA, with a neighborhood template that includes a cell and its immediate neighbors to the left and right, there will be 8 possible neighborhood states (000....111) and for each we must explicitly state whether the cell itself will map to a 1 or a 0, implying that there will be $2^{2^3} = 256$ possible local physics under these constraints. For an 8-state, nearest neighbor 2D CA, there will be 8^5 possible neighborhood states, and a choice of 8 states to map to for each of those, yielding a total of 8^{8^5} or 8^{32K} possible physics.

A good deal of work in CA has been devoted to understanding what classes of behavior and/or structure might be found in such astronomically large spaces of possible local physics. The lambda parameter form will allow you to "walk around" in a large space of possible CA rules, sampling the different kinds of behavior to be found.

For convenience, let d = dimension, k = states, r = radius.

A d-dimensional cellular automata take as their underlying space the lattice (Z = integers, infinite in both positive and negative directions) where Σ is a finite set of k elements. The dynamics are determined by a global function.

$$\Phi : \Sigma^Z \rightarrow \Sigma^Z \qquad (1)$$

whose dynamics are determined "locally" as defined below.

A "local (or neighborhood) function" ϕ is defined on a finite region

ECANS has only firing state or rest state, so strength of output is measured by firing frequency of output neuron. Throughout the experiment, ECANS can be applied to the control problem of robot, and more research is in progress.

6. Discussion and future work

ECANS is attempt to construct efficient neural network that is similar to brain model of living things. Proposed method is different from conventional neural network. After the first artificial life workshop in 1987, a large number of scientists understand that natural phenomenon of living things are able to be a base of science and engineering field. After that, the study of artificial life is very active. In recent years, new idea which is modeled natural living things has been suggested.

Authors had been studying to optimization of neural networks' structure, and we consider the new type of neural networks which is more efficient and excellent performance. So we study bio-inspired neural networks, this is ECANS.

In ECANS model, development(ontogeny) and evolution(phylogeny) are modeled by Cellular Automata that and genetic algorithms. And neuron of ECANS is used chaotic neuron model which has characteristics of animal's neuron. we verify the capability of the ECANS by applying to several problem. However proposed method still has some following problem.

1. How to connect input/output to the network?
2. How to control the developmental level?
3. What kind of cells is selected to use?
4. Is evolutionary process proper?
5. How can we make an artificial system such as brain with proposed method?

This topic is needed more research work. And we think that the fusion of cellular automata and L-system that is model the biological growth of plant is worth while to study. Real brain information processing system(neural system) is consist of three type of neuron, that is sensory neuron, motor neuron, and information processing neuron. It is expected that connection of sensory neuron and motor neuron are modeled by L-system well.

7. Conclusion

In this paper, we propose the new method of constructing neural networks modeled on development and evolution of living things. A complete mechanism of a brain has not been revealed yet. But in our study, we catch idea from the basic principle of nature that is development and evolution, and verify the effectiveness and the capability of the proposed system. Our System(Evolving Cellular Automata Systems) is named in a word ECANS for convenient.

Biological development is modeled by Cellular Automata that is a discrete dynamic system, and evolution is modeled by Genetic Algorithms. A cell(neuron) of ECANS is used Nagumo-Sato's chaotic neuron model that is deep consideration model of animal's neuron. Thus, it has complex characteristics, nevertheless it has simple structure comparatively. This chaotic neuron has firing state and rest state like biological neuron, so strength of output is measured by firing frequency of output neuron. The connection of these neuron is one of excitatory synapse, inhibitory synapse, and no connection.

We verify the ability of pattern classification of XOR and 3bit parity problem which is not classified linearly. And in order to know the memory and nonlinear mapping capability, we also apply it to robot's navigation problem. This paper is first result of out study, so the model and experiment are preliminary. For the future, we have plan to study remain problems such as input/output connecting problem, control of development level, grouping of several module, and change of neuron parameter for adaptation ability etc..

Acknowledgements

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