'94 KACC (1994. 10. 17 ~ 20)

On Autonomous Decentralized Evolution of Holon Network

Noriyasu HONMA*, Mitsuo SATO**, Kenichi ABE* and Hiroshi TAKEDA***

*Dept. of Electrical Eng.,Faculty of Eng.,Tohoku Univ.,
Aoba,Aoba-ku,Sendai 980-77,JAPAN
**Dept. of Telecommunication Eng.,Tohoku Institute of Technology,
Yagiyama,Taihaku-ku,Sendai 982,JAPAN
***Dept. of Electrical Eng.,Faculty of Eng.,Tohoku Gakuin Univ.,
1-13-1 Chuuo,Tagajo 985,JAPAN

Abstract: The paper demonstrates that holon networks can be used effectively for the identification of nonlinear dynamical systems. The emphasis of the paper is on modeling of complicated systems which have a great deal of uncertainty and unknown interactions between their elements and parameters.

The concept of applying a quantitative model building, for example, to environmental or ecological systems is not new. In a previous paper we presented a holon network model as an another alternative to quantitative modeling. Holon networks have a hierarchical construction where each level of hierarchy consists of networks with reciprocal actions among their elements. The networks are able to evolve by self-organizing their structure and adapt their parameters to environments. This was achieved by an autonomous decentralized adaptation algorithm.

In this paper we propose a new emergent evolution algorithm. In this algorithm the initial holon networks consists of only a few elements and it grows gradually with each new observation in order to fit their function to the environment. Some examples show that this algorithm can lead to a network structure which has sufficient flexibility and adapts well to the environment.

1 Introduction

The necessity to control large-scale and complicated nonlinear dynamical systems is increasing.

For the problem of grasping the behavior of nonlinear systems, in a previous paper we proposed holon networks being able to self-organize their structure and adapt their parameters to environments[1]. The *evolution* of the networks was achived by an autonomous decentralized adaptation algorithm.

Holon networks, being constructed by a number of elements and hence having high degree of parameter freedom, have great flexibility of their functions. But, at the same time, such networks are computationally expensive.

In this paper we present a new evolution algorithm to reduce the computation times. In this algorithm the initial holon network consists of only a few elements and it grows gradually with each new observation in order to fit its function to the environment. It is shown for output estimation problems of sequential circuits that this algorithm leads to a network structure which adapts well to the environment(output series) and acquires the environmental dynamics.

2 Holon network

One of the common properties of the nonlinear systems, including natural or artificial systems, for instance atmospheric phenomena, economical systems and social systems, is that nonlinear systems have complicated reciprocal actions among a lot of elements constructing the whole systems.

The concept of representing the property using a holon character has been proposed as holonic control and holonic loop[5].

The purpose of holon networks is to realize the concept as a model with respect to the input-output relation of the complicated systems.

2.1 Fundamental properties of holon networks

First, the structure of holon networks is *open-end* multi level hierarchical construction where each level of hierarchy consists of networks constructed by the elements connecting each other within the level (see fig.1).

Second, holon consisting the networks is kind of like sub-whole, having a dual character. One side of the dual character is the phase of under controlled behavior by integrated whole system to

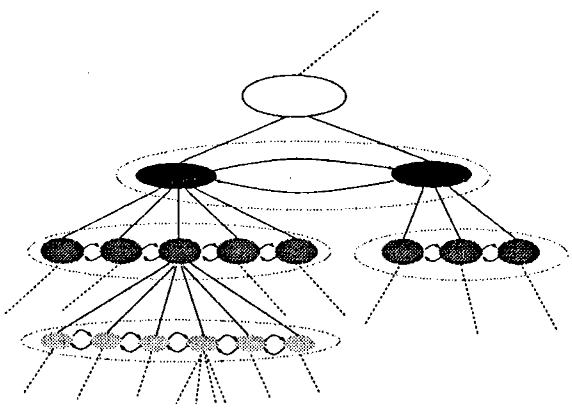

Fig. 1: Open-end multi level hierarchical construction.

which the holon belongs, other side is the phase of maintaining itself each individual autonomy as a like whole[4]. We call *dependent phase* for the former, *autonomous phase* for the latter respectively.

And last, the function of a holon is defined as the function of the network consisted by its lower level holons, on the other hand the network structure is changed by balance of the dual character of each holon.

In holon networks the dual character acts as the forces of making two reciprocal actions, which are complementary to each other and important factors in technological application. One of the reciprocal actions of holon networks, called *vertical* interaction, is the interaction between a holon and the holons within the network defining the function of the holon, and other reciprocal action, called *horizontal* interaction, is the interaction between holons within a layer.

Finally, the function of a holon, being constructed by a number of lower level layer holons, have great flexibility. Hence the function of a high level holon is able to realize great adaptability to its environment even if the function of lower holon is comparatively simple one.

2.2 Binary holon networks

As mentioned above, the structure of a holon network is the *open-end* hierarchical construction. But, the *open-end*, i.e. infinite construction cannot be realized by material construction. Hence we consider a finite hierarchical construction with material holons and an infinite hierarchical construction with imaginary holons. We call the former material holon network and the latter hidden holon network(see fig.2).

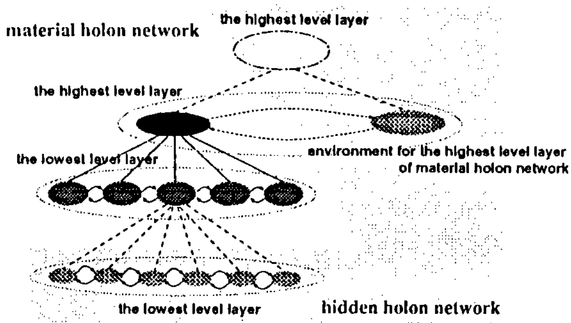

Fig. 2: Material holon network and hidden holon network.

One of the final purposes of building the holon network model is to define, on the model, explicitly quantitative two reciprocal actions, especially the *vertical* interaction. However, as the first model, we employ *binary* holon networks: each variable of the holon consisting of the networks takes *binary* values and in this paper, the material holon networks are constructed by two level layers.

The binary holon networks have many points of similarity to *random boolean networks*[2] or *cellular automata*[3]. The state transition rule of the lowest level layer holon is described by

$$x_i(t+1) = B_i\{x_i(t), w_{i1}(t)y_1(t), \cdots, w_{iN}(t)y_N(t), u_i(t)\} \quad (1)$$

$$y_i(t) = x_i(t) \qquad (i = 1, \cdots, N) \quad (2)$$

where N is the number of the lower level layer holon, $u_i, y_i, x_i (\in \{0,1\})$ denote input, output, state of the lowest layer holon i respectively, the B_i is boolean function, and the $w_{ij} (\in \{0,1\})$ denotes connection weight from the holon j to the holon i(see fig.3). In binary holon networks, the network structure of a layer is decided by the values of the w_{ij}.

The highest level holon is defined as the network constructed by the lowest level layer holons, and its output $\hat{y}$ is defined as

$$\hat{y}(t) = h\{y_1(t), \cdots, y_N(t)\} \quad (3)$$

where h is a boolean function. We define the output of a holon network as the output of its the highest level holon, $\hat{y}$.

The $\hat{y}$ varies depending on the lowest level layer holons: boolean function B_i, the w_{ij} defining the

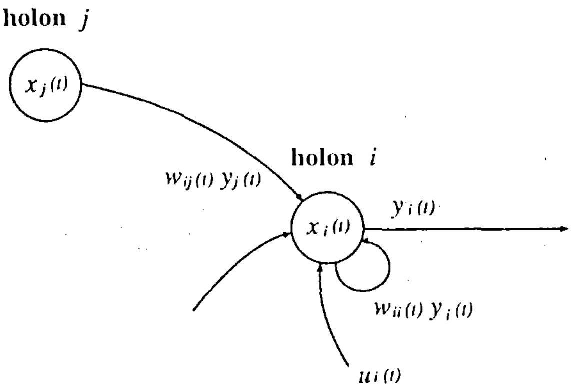

Fig. 3: Input-output relation of the lowest level layer holon i.

horizontal interaction among the lowest holons, and the initial state x_i^0.

2.3 Parameterizing the dynamics of binary holon networks

In random boolean networks, the complexity of their dynamical behavior changes depending on the parameter K which is the number of elements linked to per element[2]; it is kind of *neighbors* in cellular automata. On the other hand, in cellular automata, the complexity is changed by the parameter λ which is complexity of transition function[3]; it is related to ***biases*** in boolean networks.

The main differences from boolean networks and cellular automata are that in binary holon networks each element(the lowest level layer holon) may have individual number of linked elements and individual transition function different from each other's. (Of course, this fact don't imply that all elements must have different linked number and boolean function from each other.)

Therefore, for parameterizing the dynamics of binary holon networks, we will employ parameters: k_i[1](called the individual connection intensity) and F_r instead of the K and the λ respectively.

The k_i, implying the number of holons linking to the lowest level holon i, is defined as follows.

$$k_i = \sum_{j=1}^{N} w_{ij}. \tag{4}$$

In this paper, we will employ as the B_i four boolean functions: AND, OR, XOR(means exclusive or) and $\overline{XOR}$. Then, the parameter F_r is defined as the number of the lowest level holons which have XOR or $\overline{XOR}$ boolean functions.

$$F_r = \sum_{i=1}^{N} F_i \tag{5}$$

where $F_i = 1$ when B_i is XOR or $\overline{XOR}$, and $F_i = 0$ when B_i is AND or OR.

3 Autonomous decentralized evolution

In this section, we propose an autonomous decentralized evolution method of holon networks. First, for the $N = 20$ networks, we present a brief quantitative overview of the structural relations among the dynamical regimes in rule space of binary holon network as revealed by the k_i and the F_r parameters. Second, an autonomous decentralized adaptation algorithm is described by using these structural relationships and the holon's character.

3.1 Quantitative overview of binary holon network dynamics

We measure the complexity of binary holon networks dynamics by using Shannon's entropy H and *pseudo* Lyapunov exponent λ'[6].

For a discrete process A of S states, Shannon's entropy H is given by

$$H(A) = \sum_{i=1}^{S} p_i \log p_i. \tag{6}$$

Fig.4 shows the average entropy per the lowest level holon, $\bar{H}$, as a function of the average connection intensity per the lowest level holon, $\bar{K}$, for different values of F_r. The $\bar{K}$ given as follows.

$$\bar{K} = \frac{1}{N} \sum_{i=1}^{N} k_i. \tag{7}$$

First, note that the markable feature at around $\bar{K} = 2$ for all F_r values. The resemble result to this feature has been reported in random boolean networks[2].

Second, note that as F_r increase, $\bar{H}$ also increase for most of $\bar{K}$ points except for around $\bar{K} = 2$ and $\bar{K} = N$. Again, resemble results to those observations have been presented in cellular automata. This becomes more clearly by plotting $\bar{H}$ as a function of F_r: the function, having same feature or shape comparing with as a function of λ, is given[3] (see fig.5).

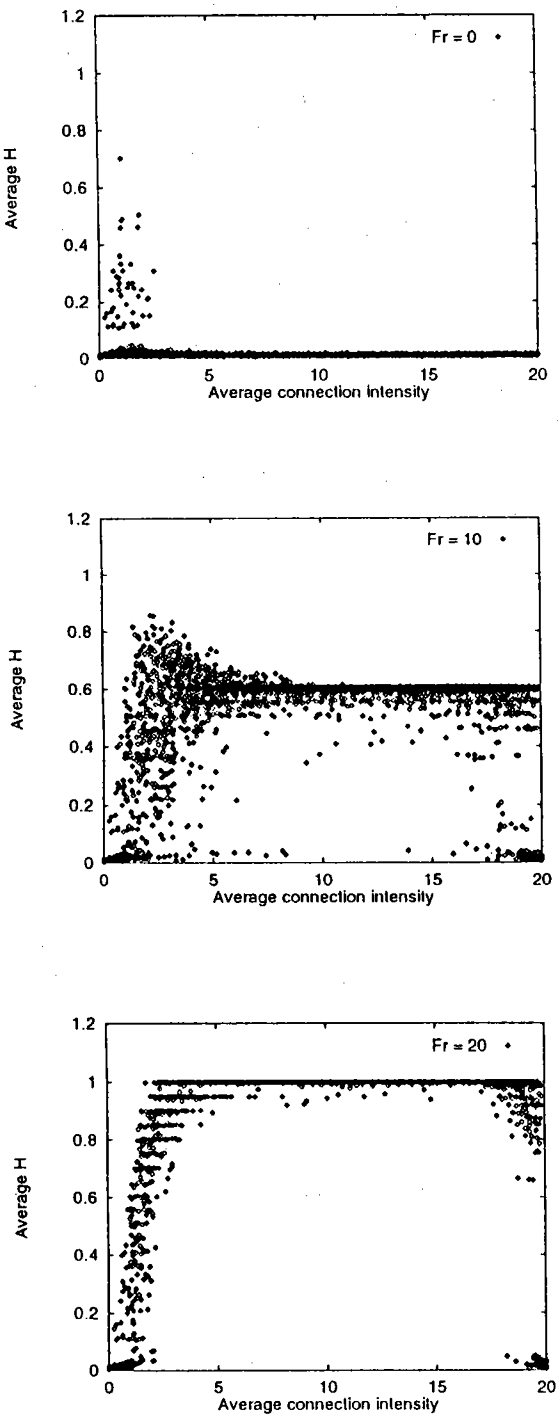

Fig. 4: Average single holon entropy $\bar{H}$ over $\bar{K}$ space for approximately 2000 binary holon network runs. Each point represents a different network structure: different arrangement of boolean functions and weight of connection lines.

In order to measure the complexity with respect to chaotic behavior depending on structural perturbation, we employ Lyapunov exponent for a binary time series, in this paper we call *pseudo* Lyapunov exponent, λ'. The λ' is defined as follows. We define a state vector X as follows.

$$X = [x_0, x_2, \cdots, x_N]^T \tag{8}$$

where x_i denotes the state of lowest level layer holon i.

Setting an initial state vector X_a^0 to a network, we observe the state vector transitions X_a^1, X_a^2, $\cdots$, X_a^M without any inputs coming from outside of the network: called *autonomous network*.

At each step $m(= 1, 2, \cdots, M)$, setting the state vector X_b^{m-1} to the network, provided the Hamming's distance from X_a^{m-1} is equal to 1, we observe one autonomous transition step and calculate the Hamming distance H^m between X_a^m and X_b^m.

For some state vector X_b^{m-1}, we calculate ensemble average of the distance H^m, $< H^m >$. Then

$$\lambda' = \lim_{M\to\infty} \frac{1}{M} \sum_{m=1}^{M} \log < H^m > . \tag{9}$$

Fig.6 shows *pseudo* Lyapunov exponent, λ', as a function of F_r. Note that fig.6 is similar to fig.5. And we observe same similarity with respect to parameter $\bar{K}$. But, λ' is not completely equal to $\bar{H}$. Fig.7 shows relation between $\bar{H}$ and λ'. This figure suggests that binary holon networks around $\lambda' = 0$(called *the edge of chaos*) are able to realize behavior with from high entropy(*chaotic or complex behavior*) to low entropy(*simple behavior*).

Therefore, if we keep a binary holon network to the edge of chaos, then we can expect high efficient adaptation ability to the process with from high complexity to low complexity. The following evolution algorithm uses this feature of binary holon network as main strategy for adaptation to environment.

3.2 Autonomous decentralized adaptation algorithm

Here, we present an autonomous decentralized adaptation algorithm for evolution of binary holon networks. In this evolution algorithm the initial holon networks consists of only a few elements. It grows gradually with each new observation in order to fit its function to environment.

In each generation τ, the connection intensities k_i which are main parameters of the algorithm, are

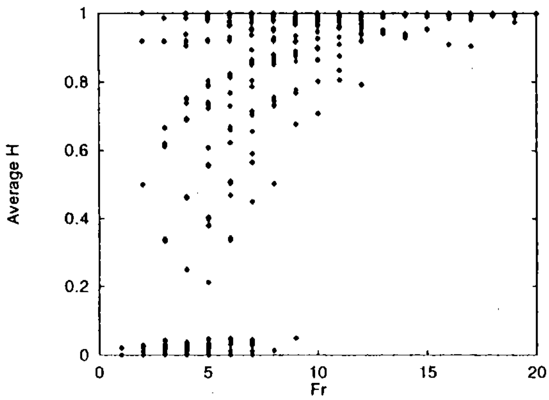

Fig. 5: Average entropy $\bar{H}$ over F_r space.

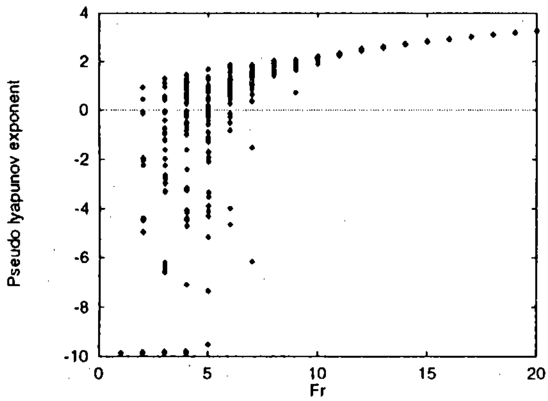

Fig. 6: *Pseudo* Lyapunov expnent λ' over F_r space.

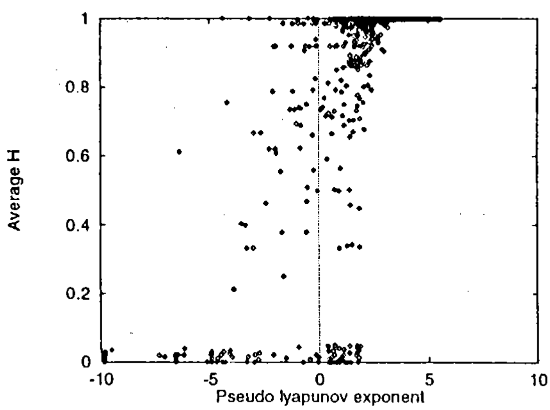

Fig. 7: Average entropy $\bar{H}$ versus *pseudo* Lyapunov expnent λ'.

changed by balance of the two phases of holon. The change in connection intensity, δk_i, is calculated as follows.

$$\begin{aligned}\delta k_i(\tau) &= \delta\bar{K}(\alpha)\{f_H(H) + f_{\lambda'}(\lambda')\}f_k(k_i) \\ &= \frac{N\{C(H_o - H_h) - \lambda'\}f_k(k_i)}{1 + exp\frac{(\alpha(\tau)-0.5)}{grad}}\end{aligned} \qquad (10)$$

More details with respect to exerting of the dual character of a holon are follows.

Throughout for all holon, the *dependent phase* of a holon against its higher level holon is affected by the *autonomous phase* of the higher holon, while the two phases of a holon are independent phases to each other[4].

The *dependent phase* of the highest level holon works to improve fitness to the environment. This phase has influence on $\delta\bar{K}$ and f_H in equation (10) as follows.

$$\delta\bar{K}(\alpha) = \frac{N}{1 + exp\frac{(\alpha(\tau)-0.5)}{grad}} \qquad (11)$$

$$f_H(H) = C(H_o - H_h) \qquad (12)$$

where $grad$ and C denote constant coefficients, the H_o and H_h denote entropy of output time series of environment and holon network respectively. Note $\delta\bar{K}$ and f_H have influence on indirectly the δk_i as coefficient.

The *autonomous phase* of the highest level holon works to keep the networks at the edge of chaos. This *autonomous phase* has influence on the *dependent phase* of its lower level layer holon as $f_{\lambda'}(\lambda') = -\lambda'$ in equation (10).

The *autonomous phase* of the lowest level holon works to keep present *state*: B_i and k_i. This *autonomous phase* has influence on $f_k(k_i)$ in equation (10) as follows.

$$f_k(k_i) = \begin{cases} 1 + k_i - kc_i \ (C(H_o - H_h) - \lambda' > 0) \\ 1 + kc_i \ \ (C(H_o - H_h) - \lambda' \leq 0) \end{cases}$$

where kc_i is defined as follows.

$$kc_i = \sum_{j=1}^{N} w_{ij}F_j. \qquad (13)$$

Finally, we present the evolution algorithm as the following:
step 1: Get a holon network of initial generation, by taking $N = 1$ and setting randomly B_1, w_{11}, x_1^0.
step 2: In each generation τ, calculate fitness $\alpha(\tau)$ to its environment(see equation (16)).
step 3: Compute $\delta k_i(\tau)$ by equation (10).

step 4: If $k_i(\tau)+\delta k_i(\tau)$ is less than $N-F_r$ or not less than F_r, then generate one the lowest level holon and $\delta k_i(\tau)=0$. The boolean function of generated holon, B_N, is decided by sign of $\delta k_i(\tau)$ as follows.

$$B_N = \begin{cases} XOR \ or \overline{XOR} & (\delta k_i > 0) \\ OR \ or AND & (\delta k_i \leq 0) \end{cases}$$

step 5: Increase w_{ij} randomly, under $\delta k_i(\tau)$ conditions: if $\delta k_i > 0$ then increase kc_i, else increase $k_i - kc_i$.
step 6: After for all $i = 1, 2, \cdots, N$ execute from *step 3* to *step 5*, go back to *step 2* at next generation $\tau + 1$.

4 Simulation results

Here, we use as a dynamical system the following sequential circuit:

$$x(t+1) = f\{x(t), u(t)\} \quad (14)$$
$$y(t) = g\{x(t), u(t)\} \quad (15)$$

where $u, y, x (\in \{0,1\})$ denote input, output, state vector of the system respectively, and a transition function f and an output function g are unknown boolean functions.

The input-output sequences of the above system are fed to our holon network.

In this simulation the fitness $\alpha(\tau)$ is defined as follows.

$$\alpha(\tau) = 1 - \frac{1}{D} \sum_{t=\tau-D+1}^{\tau} |y(t) - \hat{y}(t)| \quad (16)$$

Fig.8 shows the fitness as a function of evolutional generations. Despite change of environment(i.e. the functions f and g) at the 80 generation, the fitness converges optimal value effectively.

The fact that the fitness is maintained at the optimal value for some generations suggests that holon network acquires dynamics of the sequential circuit not only static mapping from input sequence to output sequence of the circuit. And the efficient adaptation to changing environment suggests that the new evolution algorithm can reduce the expensive computation times.

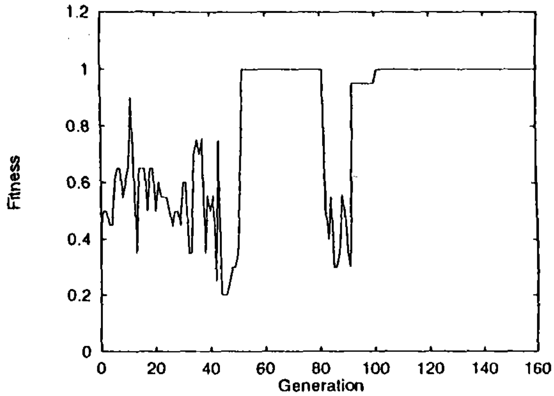

Fig. 8: Fitness as a function of generations for adaptation problem to sequential circuits dynamics.

5 Conclusion

It is shown that holon networks are useful for modeling of complicated nonlinear dynamical systems. Holon networks have great deal of flexibility and adaptability by using the evolution algorithm. The main concept of the algorithm is to keep balance of the two phases of holon. Using the new algorithm presented in this paper, it is possible to reduce the expensive calculation times. Furthermore, we are studying on more quantitative analysis of the dual character of holon and on building the continuous value holon networks.

References

[1] N.Homna, M.Sato, K.Abe and H.Takeda : Identification of Nonlinear Dynamical System with Autonomous Decentralized Adapting Methods using Holon Network Model, Preprints of The 36th Japan Joint Automatic Control Conference, 141/142 (1993)

[2] S.A.Kauffman : Antichaos and Adaptation, Scientific American, August(1991)

[3] C.G.Langton : Computation at the Edge of Chaos: Phase Transitions and Emergent Computation, Physica D 42 12/37 (1990)

[4] A.Koestler : Janus, Kousakusya (1983)

[5] H.Simizu : Life and Place, NTT Publishing Co.,Ltd. (1992)

[6] K.Ito : The Border between Order and Chaos – An Approach to a New Technology to Imitate the Autonomous Evolution of Life –, J.SICE 32-9, 768/775 (1993)