Multiple Chaos Generator by Neural-Network-Differential-Equation for Intelligent Fish-Catching

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Abstract: Continuous catching and releasing experiment of several fishes make the fishes find some escaping strategies such as staying stationary at corner of the pool. To make fish-catching robot intelligent more than fishes' adapting and escaping abilities from chasing net attached at robot's hand, we thought something that goes beyond the fishes' adapting intelligence will be required. Here we propose a chaos-generator comprising NNDE (neural-network-differential-equation) and an evolving mechanism to have the NNDE generate chaotic trajectories as many as possible. We believe that the fish could not be adaptive enough to escape from chasing net with chaos motions that have much different chaos, since unpredictable chaotic motions of net may go beyond the fishes' adapting abilities to the net motions. In this report we introduce the chaos generating system by NNDE, which can produce many kinds of chaos theoretically, and then analyze the chaos with Lyapunov number, Poincare return map and initial value sensitivity.

Key words: Chaos, neural network, genetic algorithm.

1. Introduction

In recent years, visual tracking and servoing in which visual information is used to direct the end-effector of a manipulator toward a target object has been studied in some researches [1, 2]. A new trend of machine intelligence [3] that differs from the classical AI has been applied intensively to the field of robotics and other research areas like intelligent control system. Typically, the animal world has been used conceptually by robotics as a source of inspiration for machine intelligence. For the purpose of studying animal behavior and intelligence, the model of interaction between animals and machines is proposed in researches like Ref. [4]. In their previous research, the fish emotional behavior has also been examined and the robot with adaptive ability to react to the fish status has been conceived. Another crucial

characteristic of machine intelligence is that the robot should be able to use input information from sensor to know how to behave in a changing environment and furthermore can learn from the environment for safety like avoiding obstacle. As known universally that the robot intelligence has reached a relatively high level, still the word "intelligence" is an abstract term, so the measurement of the intelligence level of a robot has become necessary. A practical and systematic strategy for measuring MIQ (machine intelligence quotient) of human-machine cooperative systems is proposed in Ref. [5]. In our approach to pursue intelligent robot, we will evaluate the intelligence degree between fishes and the robot by Fish-Catching operation. we think that the system combined with chaos is smarter than the fish when the robot can beat the fish by catching it successfully even after the fish finds out some reached a relatively high level, still the word "intelligence" is an abstract term, so the measurement of the intelligence level of a robot has become

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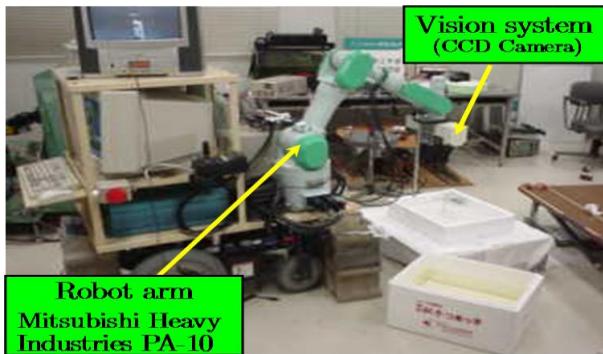
Fig. 1   Fish catching system PA10.

necessary. A practical and systematic strategy for measuring MIQ (machine intelligence quotient) of human-machine cooperative systems is proposed in Ref. [5]. In their approach to pursue intelligent robot, we will evaluate the intelligence degree between fishes and the robot by Fish-Catching operation. We think that the system combined with chaos is smarter than the fish when the robot can beat the fish by catching it successfully even after the fish finds out some escaping strategy. As we did not find the research about the intelligence comparison between animal and robot, we mainly dedicate ourselves to constructing a smart system that is more intelligent than the fish. We consider that the competitive relation can be very meaningful as one way to discuss robotic intelligence. So we not only employ the inspiration of animal's behavior for robot intellectualization, we can also conceive a robot that can exceed the animal intelligence. By evolutionary algorithms [6], Visual Servoing and Object Recognizing based on the input image from a CCD camera mounted on the manipulator has been studied in their laboratory (Fig. 1) [7], and we succeeded in catching a fish by a net attached at the hand of the manipulator based on the real-time visual tracking under the method of Gazing GA [8] to enhance the real-time searching ability.

We have learned that it is not effective for fish catching to simply pursue the current fish position by visual servoing with velocity feedback control. Actually, the consistent tracking is sometimes impossible because the fish can alter motion pattern suddenly maybe under some emotional reasons of fear. Those behaviors are thought to be caused by emotional factors and they can also be treated as a kind of innate fish intelligence, even though not in a high level.

While observing the fishes' adapting behavior to escape in the competitive relations with the robot, that is continuous catching/releasing experiments, We found that we can define a "FIQ" (fish's intelligent quotient) [9] representing decreasing velocity of fish number caught by the net through continuous catching/releasing operation. Through this measure we can compare the innate intelligence of the fish and the artificial intelligence of the robot.

It has been well known that many chaotic signals exist in our body, for example, in nerves, in motions of eye-balls and in heart-beating periods [10, 11].

Therefore we thought that imitating such animal's internal dynamics and putting chaos into robots have something meaningfulness to address fishes' intelligence. We embed chaos into the robot dynamics in order to supplement the deficiency of their Fish-Catching system [12].

Therefore what we have to pay attention to the fishes' nature that the fish does conceive always escaping strategy against new stressing situation. This means that robot's intelligence to override the fishes' thinking ability needs infinite source of idea of catching motions. To generate such catching motion, we propose in this report NNDE (neural-network-differential-equation) that can produce neural chaos and inherently have a possibility to be able to generate infinite varieties of chaos, derived from the neural network's ability to approximate any nonlinear function as accurate as with desirable precision [13-15].

This paper is organized as follows: Section 2 discusses the fish tracking and catching; Section 3 introduces the problem of fish-catching; Section 4 defines fish intelligent quotient; Section 5 verifies the validity of chaos; Section 6 shows neural-network-differential-equation; Section 7

explains chaos verification methods; Section 8 proposes the chaos generate system; Section 9 gives the verification results of chaos; Section 10 discusses sensitivity of neuron's weight; Section 11 concludes this paper.

2. Fish Tracking and Catching

The problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of $r(t) = [x(t), y(t)]^T$ in order to maximize $F(r(t))$, where $F(r(t))$ represents correlation function of images and fish-shaped matching model. $F(r(t))$ is used as a fitness function of GA [8]. To recognize a target in a dynamic image input by video rate, 33 [fps], the recognition system must have real-time nature, that is, the searching model must converge to the fish in the successively input raw images. An evolutionary recognition process for dynamic images have been realized by such method whose model-based matching by evolving process in GA is applied at least only one time to one raw image input successively by video rate. We named it as "1-Step GA" [7]. When the converging speed of the model to the target in the dynamic images should be faster than the swimming speed of the fish in the dynamic images, then the position indicated by the highest genes represent the fish's position in the successively input images in real-time. We have confirmed that the above time-variant optimization problem to solve $r(t)$ maximizing $F(r(t))$ could be solved by "1-Step GA". $r(t) = [x(t), y(t)]^T$ represents the fish's position in Camera Frame whose center is set at the center of catching net, then $r(t)$ means position deviation from net to fish, means $r(t) = \Delta r(t)$. The desired hand velocity at the i-th control period $\dot{r}^i{}_d$ is calculated as

$$\dot{r}^i{}_d = K_P \Delta r^i + K_V (\Delta r^i - \Delta r^{i-1}) \qquad (1)$$

where, Δr^i denotes the servoing position error detected by 1-Step GA [7]. K_P and K_V given are positive definite matrix to determine PD gain. Now we add chaos items to Eq. (1) above, and we also need to redefine the meaning of $\dot{r}^i{}_d$.

The simple PD servo control method given by Eq. (1) is modulated to combine a visual servoing and chaos net motion into the controller as follows

$$\Delta r^i = k_1 \cdot \Delta r^i{}_{fish} + k_2 \cdot \Delta r^i{}_{chaos} \qquad (2)$$

Here $\Delta r^i{}_{fish} = [\Delta x^i{}_{fish}, \Delta y^i{}_{fish}]^T$, is the tracking error of fish from the center of camera frame, and $\Delta r^i{}_{chaos} = [\Delta x^i{}_{chaos}, \Delta y^i{}_{chaos}]^T$ denotes a chaotic oscillation in $x - y$ plane around the center camera frame. Therefore the hand motion pattern can be determined by the switch value k_1 and k_2. $k_1 = 0$ and $k_2 = 0$ indicate visual servoing, and $k_1 = 0$ and $k_2 = 1$ indicate the net will track chaotic trajectory made by NNDE being explained later in this report. The desired joint variable $\dot{q}_d$ is determined by inverse kinematics from $\dot{r}_d$ by using the Jacobian matrix $J(q)$ and is expressed by equation

$$\dot{q}_d = J^+(q)\dot{r}_d \qquad (3)$$

where, $J^+(q)$ is the pseudo inverse matrix of $J(q)$. The robot used in this experimental system is a 7-Link manipulator, Mitsubishi Heavy Industries PA-10 robot.

3. Problem of Fish-Catching

In order to check the system reliability in tracking and catching process, we kept a procedure to catch a fish and release it immediately continuously for 30 min. We released 5 fishes (length is about 40 mm) in the pool in advance, and once the fish got caught, it would be released to the same pool at once. The result of this experiment is shown in Fig. 2, in which vertical axis represents the number of fishes caught in successive 5 min and horizontal axis represents the catching time. We had expected that the capturing operation would become smoother as time passing on consideration that the fish may get tired. But to their astonishment, the number of fishes caught decreased gradually.

The reason of decreased catching number may lie in the fish learning ability. For example, the fish can learn how to run away around the net as shown in
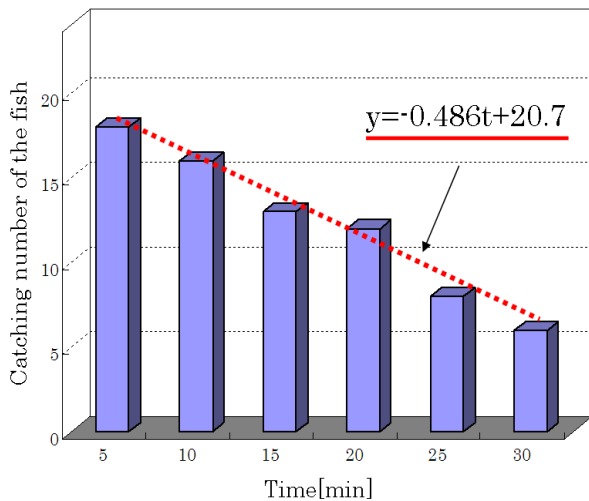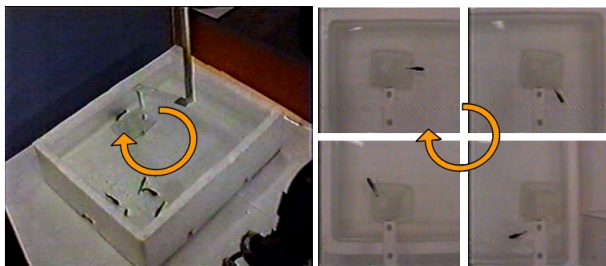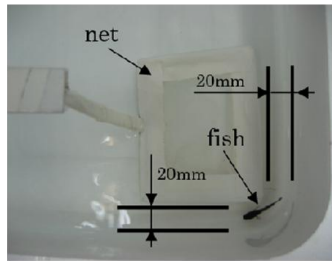
Fig. 2   Result of fish catching.

(a) Motion 1 of a fish

(b) Motion 2 of a fish   (c) Motion 3 of a fish

Fig. 3   Fish motion.

Fig. 3a by circular swimming motion with about constant velocity, having made a steady state position error that the net can not reach to the chasing fish. Or the fish can stay in the opposite corner against the net in the pool shown in Fig. 3b. And also, the fish can keep staying within the clearance between the edge of the pool and the net shown in Fig. 3c where the net is inhibited to enter.

To solve these problems, and to achieve more intelligent fish catching systems, we thought chaos behavior of the net with many chaotic varieties can be a possible method to overcome those fishes' escaping

intelligence, since huge variety of chaos trajectories seems to be unpredictable for the fish to adapt them. This strategy to overcome fishes' adaptive intelligence is based on a hypothesis that unpredictability of the motion of the chasing net produced by plural chaos can made the fishes' learning logic confuse, getting the fish catching robot have made intelligence than the fishes'.Then we propose Neural-Network-Differential-Equation to generate chaos as many as possible.

4. Fish Intelligence Quotient

To evaluate numerically how fast the fish can learn to escape the net, we adapted Linear Least-Square approximation to the fish-catching decreasing tendency, resulting in $y = -0.486t + 20.7$ as shown in Fig. 2. The decreasing coefficient −0.486 represents adapting or learning velocity of the fishes as a group when the fishes' intelligence is compared with robotic catching. We named the coefficient as "FIQ" (Fish's Intelligence Quotient), since learning velocity has been thought as one of components of the Intelligence Quotient. The larger minus value means high intelligence quotient of the fish, zero does equal and plus does less intelligent than robot's. To overcome the fishes' intelligence, more intelligent robotic system needs to track and catch the fish effectively, in other words it comes to the problem on how to use the item Δr_{chaos}^i chaos in Eq. (2) effectively to exceed the fish intelligence.

5. Validity of Chaos

In 1982, some experiments revealed that mollusk neuron cells and plant cells have irregular excitement and show chaotic nature if gave them periodic current stimulation. In addition, also chaotic response for periodic current stimulation had been clarified in the axon of the cuttlefish in 1984. From these studies, it became clear that the chaos is associated with biology. In the late 1980s, the relationship between chaos and function of the nervous system has been discussed. Mpitosos and colleagues examined the pattern of rhythmic firing of motor neurons of sea cucumber and

showed that frequency variation of continuous discharge relates to the rhythm of the movement with chaotic behavior. Thus, chaos exists in biological behavior. It is decided whether the nerve cell of the organism is excited by a stimulation signal, and this is because it follows the theory of the chaos. Therefore, animal behavior and strategies can be estimated from point of chaos, and maybe apply to catch fish. There has been presented chaoses with a simplified model of H-H (hodgkin-huxley) model or BVP (bonhoeffer-van der pol) model. Using one chaos model to produce unpredictable motion add to catching-net behaviors seems to be effective, however we thought single chaos model is not adequate to overcome fishes' escaping idea since the fishes change their behavior continuously.

6. Neural-Network-Differential-Equation

Lorenz and Rossler models renowned as chaos generation comprise three differential equations, producing three-dimensional chaotic trajectory in phase space. Since a N.N. (neural-network) has been proven to have an ability to approximate any non-linear functions with arbitrarily high accuracy, we thought it is straightforward to make a differential equation including N.N. so that it can generate plural chaoses by changing N.N.'s coefficients. We define next nonlinear differential equation including N.N. function $f(p(t))$ as

$$\dot{p}(t) = f(p(t)). \tag{4}$$

$p(t) = [p_1(t), p_2(t), p_3(t)]^T$ is state variable. The nonlinear function of $f(p(t))$ in Eq. (4) is constituted by N.N.'s connections, which is exhibited in left part of Fig. 4 where the N.N. and integral function of outputs of N.N. and the feedback of the integrated value to the inputs of N.N. constitute nonlinear dynamical Eq. (4). We call it as Neural-Network-Differential-Equation.

7. Chaos Verification Methods

Since there have been no simple criterion to determine whether irregular oscillation should be a chaos or not, we have to apply plural evaluations over the irregularities of trajectories produced by NNDE. The followings are criteria being used for judging the chaotic characters.

7.1 Lyapunov Exponent

As one of criteria to evaluate a chaos' character of expansion in time domain, Lyapunov exponent expressed by the following equation is well known,

$$\lambda = \lim_{N \to \infty} \frac{1}{N} \sum_{i=0}^{N-1} \log|f'(x_i)| \tag{5}$$

where, positive value can represent that the irregular oscillation diverts from a standard trajectory, which expands like a function of e^{at} $(a > 0)$.

7.2 Poincare Section

The trajectories of the motion made by Neural-Network-Differential-Equation (4) is examined by using the Poincare section to verify further whether the resulted trajectories can be identified as chaos. Next, the Poincare section is explained. First of all, we examine a simple closed curve in three dimensions as shown in Fig. 5. The plane "A" that intersects with this closed trajectory pointed by "P" is defined as the Poincare section.

The intersecting points are named as $P_n, P_{n+1}, P_{n+2}, \cdots$, and corresponding x-axis position on A are $x_n, x_{n+1}, x_{n+2}, \cdots$, which are all pointed to the Poincare Return Map as $x_n, x_{n+1}, \cdots$ as shown in Fig. 6. With the Poincare return map of Fig. 6 representing a
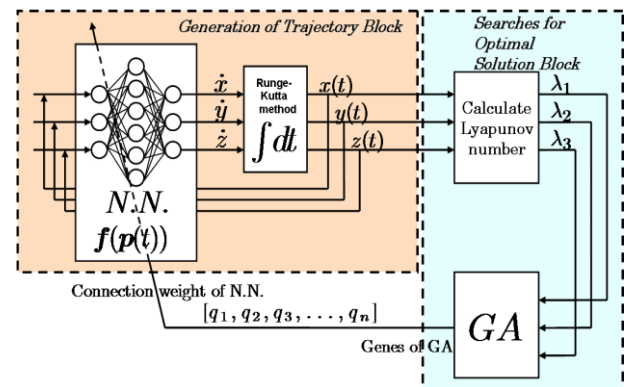
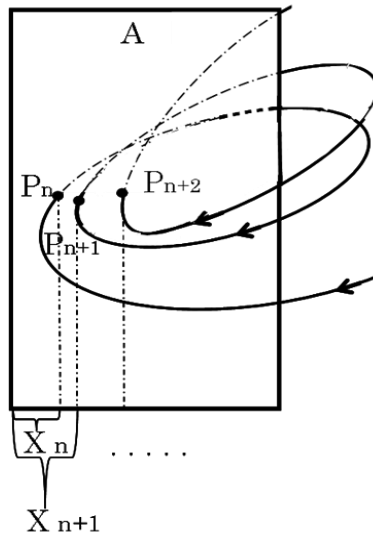

Fig. 4   Block diagram of chaos generation.
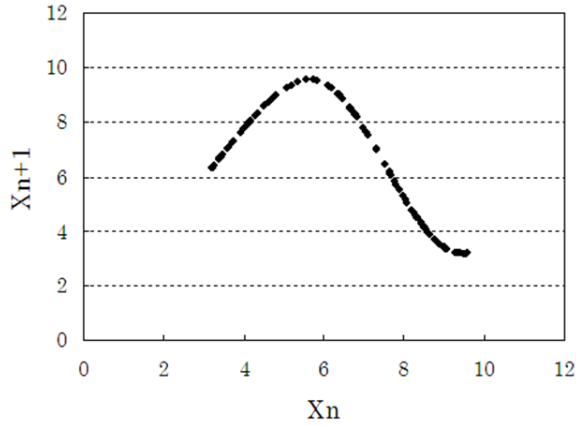
Fig. 5   Poincare section.

Fig. 6   Poincare return map.

shape of "Λ", the closed curve has the structure of stretching and folding. This structure is a basic character of chaos. Looking at the left half of Fig. 6, we can see the inclination coefficient $dx_{n+1}/dx_n > 1$ and right half has $dx_{n+1}/dx_n < -1$, representing that left half has expansion and the other does contraction.

8. Chaos Generate System

Fig. 4 represents the block diagram to find chaos by using GA and Lyapunov number. This GA is not 1-Step GA, described in Section 2 but used as a normal GA's procedure that evolves genes representing neural network coefficient's volume. The trajectory $p(t)$ in time domain obtained from Neural-Network-Differential-Equation is used for the

calculation of Lyapunov number. Here, $L = [\lambda_1, \lambda_2, \lambda_3]^T$ is a Lyapunov number. Using this L for the evolution of GA, fitness function is defined as follows,

$$g = k_1 \cdot \lambda_1 - k_2 \cdot |\lambda_2| - k_3 \cdot \lambda_3 \qquad (6)$$

This fitness function incorporated the chaotic property of the Lyapunov spectrum, which is one of factors to be essential for generating chaos trajectory. Here, because we discuss three-dimensional chaotic attractor in phase space, there are 3 Lyapunov exponents. The relationship between positive and negative Lyapunov spectrum is (+, 0, −), which means resulted time trajectory of Eq. (4) may be thought to be chaos. Parentheses indicate the sign of the Lyapunov spectrum. In other words, λ_1 is positive, λ_2 is also positive or negative small values, λ_3 is negative case, the fitness function of Eq. (6) appears to have relatively large positive value when $\lambda_1 > 0, \lambda_2 \approx 0, \lambda_3 < 0$. In addition, k_1, k_2, and k_3 are positive coefficients. The gene of GA is defined as shown in Fig. 7, with connection weights of N.N. being $q = [q_1, q_2, \cdots, q_n]^T$. In this report we adopted a network of $3 \times 6 \times 3$ as shown in Fig. 4, then the line number of connections and coefficient are 48, i.e., $n = 48$. The bit length of q is 16 bits. Because the gene is expressed in binary, converted to decimal and normalized into a range from 0 to 1. Then, generating a trajectory $p(t)$ based on a given gene having been determined by GA at one previous generation and calculating Lyapunov number, and evolving new generation of gene are repeated. This GA's evolution can find q to have a highest value of g defined by Eq. (6), which means possible chaos trajectory.

9. Verification Results of Chaos

So far we have found four chaos patterns with different neural coefficients explore by GA mentioned in the previous section. We named them with a serial number as chaos 01~chaos 04. The followings are

$$q_1 \qquad q_2 \qquad q_n$$

$$\underbrace{10011\ldots1}\ \underbrace{01001\ldots1}\ \cdots\ \underbrace{11010\ldots0}$$
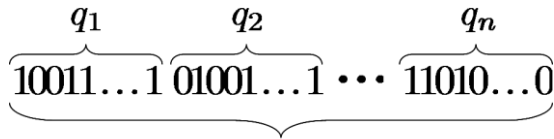
Individual Combination of Connection weight of N.N.

Fig. 7   Gene of GA.

the introduction of those chaoses with each individual character.

9.1 Chaos 01

9.1.1 Lyapunov Number

Lyapunov numbers are $\lambda_1 = 0.014585$, $\lambda_2 = -0.003314$ and $\lambda_3 = -0.165381$. These are corresponding to the Lyapunov spectrum of chaos, (+, 0, −), and the trajectory is exhibited in Fig. 8.

9.1.2 Sensitivity to Initial Value

Two time-profile of trajectories with minutely different initial value are shown in Fig. 9. The trajectories of $(x_1(t), y_1(t), z_1(t))$ are the results that originated from the initial values of $x_1(0) = 1.00, y_1(0) = 1.00, z_1(0) = 1.00$ and $(x_2(t), y_2(t), z_2(t))$ are from $x_2(0) = 1.01, y_2(0) = 1.01, z_2(0) = 1.01$. Trajectories of x_1 and x_2 are shown in Fig. 9.

We can see from Fig. 9 that the two trajectories with minute difference of initial values divert often about 800 s having passed, this means the slight different initial values make large separation with each other, indicating sensitivity of initial value, which is one of the character of chaos. As for y and z coordinates, they are similar, omitted to spare the space.

9.1.3 Poincare Return Map

Chaos 01's poincare return map is shown in Fig. 10. One dimensional map can be seen in Fig.10, from which we can understand that the map represents expanding (left half of the Fig. 10) and contracting (right half) that are essential character to generate chaos.

Therefore, the property of chaos 01 has been confirmed from the viewpoints of Lyapunov number, the sensitivity of initial value, and the Poincare return map.

9.2 Chaos 02, 03, 04

We searched second chaos by similar produce like chaos 01. Up to now we have found other three chaos, 02, 03 and 04 whose trajectories are depicted in Figs. 11-13, where Lyapunov numbers are listed in Table 1, including chaos 01 also. We confirmed all chaos trajectories have the Lyapunov spectrum of chaos, (+, 0, −).
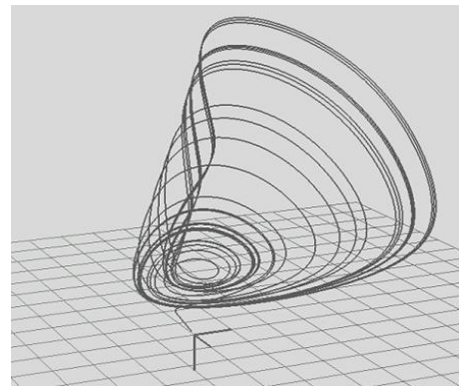

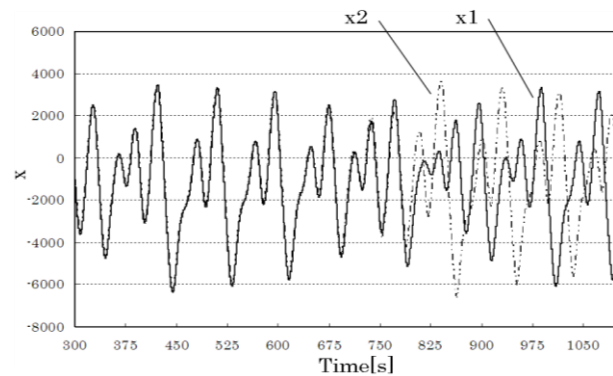**Fig. 8   Generated chaos trajectory of Chaos 01.**

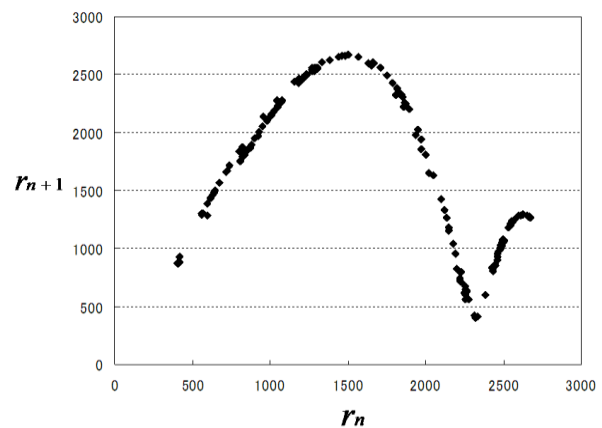**Fig. 9   Generated trajectory 01 of x (300[s] to 1100[s]).**
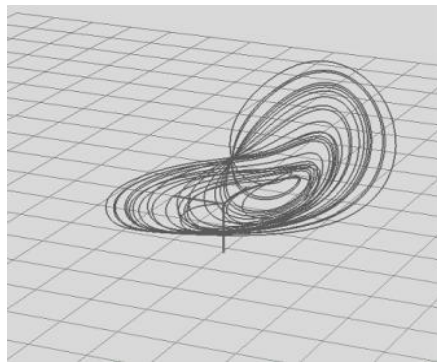

Fig. 10   Poincare return map of Chaos01.

Fig. 11   Generated chaos trajectory 02.
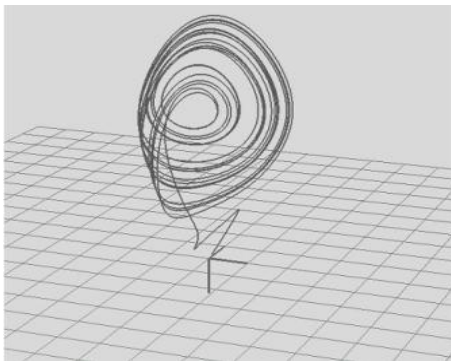

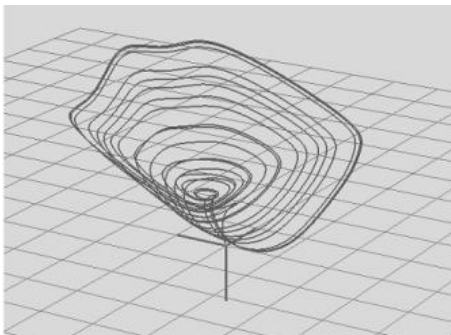**Fig. 12   Generated chaos trajectory 03.**

Fig. 13   Generated chaos trajectory 04.

10. Sensitivity of Neuron's Weight

We have noticed weight coefficient of N.N. that generated chaos 03 is almost similar to chaos 04's. That is, only one weight coefficient is different, that is "q_1" in Fig. 14. We think "q_1" is related to the generation of chaos. So we increased the weight slightly from "-1" and compare their trajectories. The range of q_1 is $-1.0 \le q_1 \le 1.0$ and q_1 is increased from -1.0 by 0.1. In the case of $-1.0 \le q_1 \le -0.4$, $0.1 \le q_1 \le 0.2$ and $0.8 \le q_1 \le 1.0$, we can not be considered that the trajectories are

semi-periodic trajectories as shown in Figs. 15-17. They indicate that the trajectories are expanded to infinity as shown in the three figures. On the other hand, the range of $-0.3 \le q_1 \le 0.0$ and $0.3 \le q_1 \le 0.7$ made chaos trajectories as shown in Figs. 18 and 19. This result indicates that continuous changing of q_1 can make various chaos, stemming from continuity of real variables. The Lyapunov number of each trajectory is shown in Table 2.

Table 1   Lyapunov number.

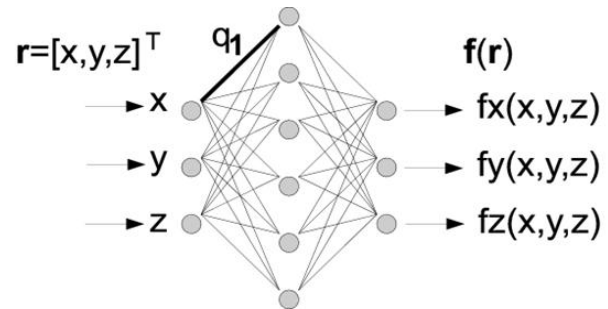|	chaos01	chaos02	chaos03	chaos04
λ_1	0.014585	0.01919	0.015934	0.01208
λ_2	-0.003314	0.00733	-0.002172	-0.00143
λ_3	-0.165381	-0.10379	-0.123026	-0.075448

Fig. 14   Neural network for nonlinear function generation.

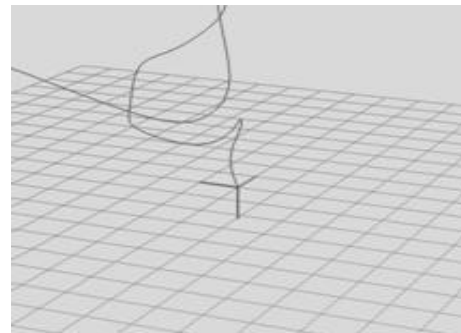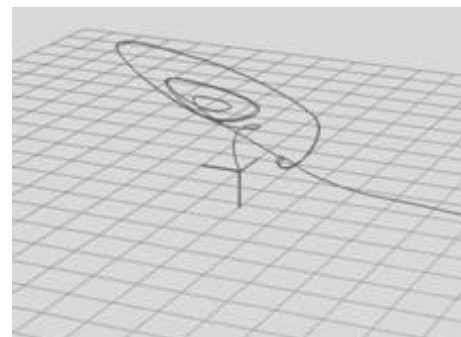**Fig. 15   Weight = -0.7.**

Fig. 16   Weight = 0.2.
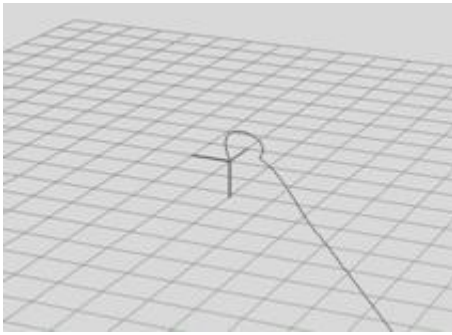
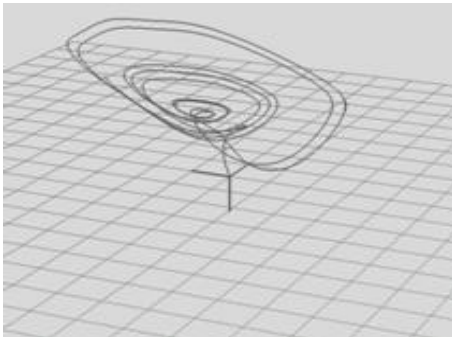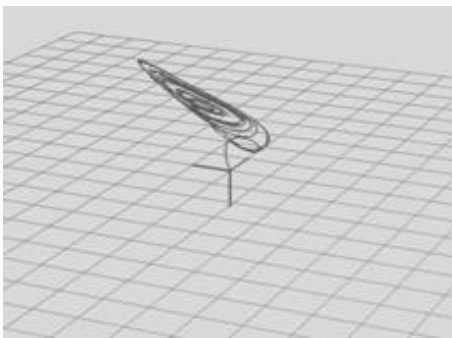**Fig. 17   Weight = 0.9.**

Fig.18   Weight = 0.0.

Fig. 19   Weight = 0.7.

Table 2   Lyapunov number.

λ $\quad q_1$	-0.7	0.0	0.2	0.7	0.9
λ_1	0.007314	0.016477	0.008571	0.004668	0.003386
λ_2	-0.004319	0.002719	-0.038939	0.011399	-0.046857
λ_3	-0.30184	-0.106123	-0.061084	-0.136963	-0.048269

11. Conclusions

This paper proposed chaos generating system composed of Neural Network and GA's evolving ability to change the Neural-Network-Differential-Equation to be able to generate chaos. This chaos generating system has exploited the neural network's

nature of approximation of any nonlinear function with any desired accuracy. We will utilize this chaos motion for overcoming fishes' escaping ability from chasing net for now.

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