Multiple Chaos Generation by Neural-Network-Differential-Equation For Intelligent Fish-Catching

Yuya Ito[1], Takashi Tomono[1], Mamoru Minami[1] and Akira Yanou[1]

[1]Graduate school of Natural Science and Technology, Okayama University, Okayama, Japan
(Tel: +81-86-251-8924; E-mail: itou@suri.sys.okayama-u.ac.jp)

Abstract: Continuous catching and releasing experiment of several fishes makes the fishes find some escaping strategies such as staying stationary at corners 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 would be required. Here we propose a chaos-generator comprising Neural-Network-Differential-Equation(NNDE) and an evolving mechanism to have the NNDE generate plural differential equations as many as possible that can yield different kind of chaos. We believe that the fish could not be adaptive enough to escape from chasing net with many different chaotic trajectories, since unpredictable chaotic motions of net may go beyond the fishes' adapting abilities. In this paper we introduce chaos-generating system by NNDE, which has a possibility to yield uncountable kinds of chaos theoretically, then analyze the chaos with Lyapunov number, Poincare return map and initial value sensitivity.

Keywords: Neural network, Chaos generator, 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 roboticists 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 [4]. A crucial characteristic of machine intelligence is that the robot should be able to use information input from sensor to know how to behave in a changing environment and furthermore can learn from the environment 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 machine intelligence quotient (MIQ) of human-machine cooperative systems is proposed in [5], which evaluates a complexity of machine's procedures. Contrarily to this approach, we measure a robot's intelligence through a comparison animal's adaptivity with the robot's.

In our approach to pursue intelligent robot, we will evaluate the intelligence degree between fishes and the robot by Fish-Catching operation. In our 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. We think that the system combined with chaos could be smarter than the fish when the robot can go beyond the fish by catching it successfully even after the fish finds out some escaping strategy. As we did not find researches about the intelligence com-
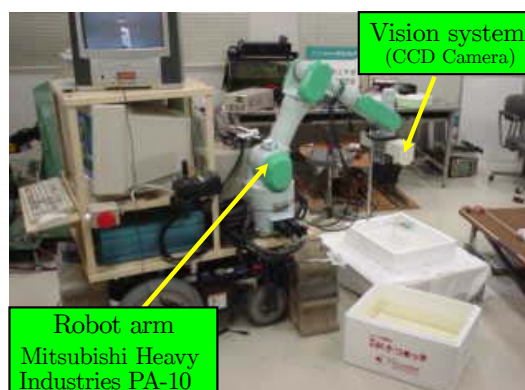

Fig. 1 Fish Catching system PA10

parison 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 improve 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 our 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 a escaping fish by visual servoing with velocity feedback control. Actually, the consistent tracking is sometimes impossible because the fish alter motion pattern suddenly maybe under some emotional reasons

of fear, thought to be a kind of innate 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 "Fish's Intelligent Quotient"(FIQ)[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 eyeballs and in heart-beating periods [10],[11]. Therefore we thought that imitating such animal's internal dynamics and putting chaos into robots have something meaningful to address fishes' intelligence. We embed chaos into the Robot Dynamics in order to supplement the deficiency of our Fish-Catching system, having resulted in proving fishes' astonishing ability to be able to adapt even to the chaotic net motion and that fishes become ignoring the net motion of single chaos.

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 Neural-Network-Differential-Equation(NNDE) 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[12][13].

2. RANDOM AND CHAOS

A random number is unpredictable. It seems that it is impossible to generate the random number by computer program, because computer program is just able to output a sequence of numbers by prescribed programs, resulting in the output number be essentially predictable. Actually, the random number generation routine in computer is called pseudorandom number, it is not real random number with genuine unpredictability. That means the pseudorandom number is predictable. A function to generate a "random number" prepared in a standard language like "C++" is based on the linear congruential method almost without exception, producing pseudorandom number of cyclic oscillation with huge cycle. This method is proposed by Lehmer, D.H. around 1948, and it's so easy and efficient for generating pseudorandom-numbers, named "linear congruential method" with the following recurrence formula [16].

$$X_n = aX_{n-1} + c \pmod{M}, n \geq 1 \qquad (1)$$

This equation can output integer pseudorandom-numbers sequence $X_0, X_1, X_2, \cdots$. The M is called modulus of congruence expression. a and c are positive integers. a is called multiplier, c is called increment. So, the remainder value, coming from $aX_{n-1} + c$ divide by M, is set
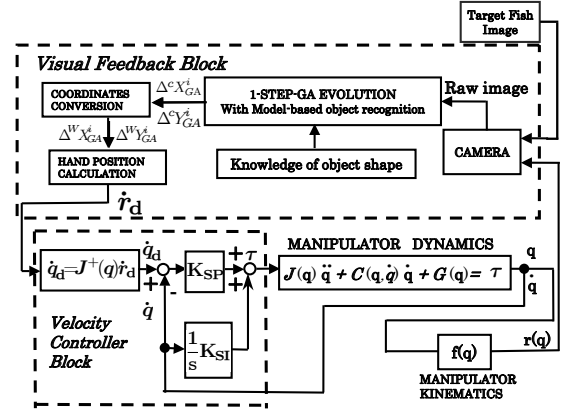

Fig. 2 Block diagram of the controller

to X_n. In eq.(1) there is a period, this period is no larger than M. If M, a, and c are chosen well combination, the maximum cycle M can be obtained. In the case of the maximum period, all the integer numbers not smaller than 0 and not larger than $M - 1$ appear in somewhere. No matter X_0, there appears the same sequence of numbers after all, and this is a periodic function.

Chaos has the character of unpredictability. This happens by negligible differences of initial positions bear unpredictable huge difference between the solved trajectories. This means that deterministic equation of chaos can generate unpredictability. The Bernoulli shift is mentioned as a typical example that realizes the character of the chaos. The Bernoulli shift is expressed by considering the variable X_i is a real number and by substituting $a = 2, c = 0$ or $-1, M = 1$ into (1).

$$X_n = \begin{cases} 2X_{n-1} & \pmod{1}, n \geq 1, (0 \leq X_{n-1} \leq 0.5) \\ 2X_{n-1} - 1 & \pmod{1}, n \geq 1, (0.5 < X_{n-1} \leq 1) \end{cases} \qquad (2)$$

That is, chaos and pseudorandom numbers can be generated by the same equation. As mentioned above, we consider that chaos and random numbers have relations of intersection.

3. FISH TRACKING AND CATCHING

The problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of $\boldsymbol{r}(t) = [x(t), y(t)]^T$ that maximizes $F(\boldsymbol{r}(t))$, where $F(\boldsymbol{r}(t))$ represents correlation function of images and fish-shaped matching model. $F(\boldsymbol{r}(t))$ 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 represents the fish's position in the successively input images in real-time.

We have confirmed that the above time-variant optimization problem to solve $\boldsymbol{r}(t)$ maximizing $F(\boldsymbol{r}(t))$

could be solved by "1-Step GA".

$\boldsymbol{r}(t) = [x(t), y(t)]^T$ represents the fish's position in Camera Frame whose center is set at to be the center of catching net, then $\boldsymbol{r}(t)$ means position deviation from net to Fish, means $\boldsymbol{r}(t) = \Delta\boldsymbol{r}(t)$.

The desired hand velocity at the i-th control period $\dot{\boldsymbol{r}}_d^i$ is calculated as

$$\dot{\boldsymbol{r}}_d^i = \boldsymbol{K}_P \Delta\boldsymbol{r}^i + \boldsymbol{K}_V (\Delta\boldsymbol{r}^i - \Delta\boldsymbol{r}^{i-1}) \qquad (3)$$

where $\Delta\boldsymbol{r}^i$ denotes the servoing position error detected by 1-Step GA [7]. $\boldsymbol{K}_P$ and $\boldsymbol{K}_V$ given are positive definite matrix to determine PD gain. Now we add chaos items to (3) above, and we also need to redefine the meaning of $\dot{\boldsymbol{r}}_d^i$. The simple PD servo control method given by (3) is modulated to combine a visual servoing and chaos net motion by redefinding $\Delta\boldsymbol{r}^i$ as,

$$\Delta\boldsymbol{r}^i = k_1 \cdot \Delta\boldsymbol{r}_{fish}^i + k_2 \cdot \Delta\boldsymbol{r}_{chaos}^i \qquad (4)$$

Here $\Delta\boldsymbol{r}_{fish}^i = \begin{bmatrix} \Delta x_{fish}^i & \Delta y_{fish}^i \end{bmatrix}$ is the tracking error of fish from the center of camera frame, and $\Delta\boldsymbol{r}_{chaos}^i = \begin{bmatrix} \Delta x_{chaos}^i & \Delta y_{chaos}^i \end{bmatrix}$ denotes a chaotic oscillation in $x - y$ plane around the center of camera frame. Therefore the hand motion pattern can be determined by the switch value k_1 and k_2. $k_1 = 1$ 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 paper. The desired joint variable $\dot{\boldsymbol{q}}_d$ is determined by inverse kinematics from $\dot{\boldsymbol{r}}_d$ by using the Jacobian matrix $\boldsymbol{J}(\boldsymbol{q})$, and is expressed by

$$\dot{\boldsymbol{q}}_d = \boldsymbol{J}^+(\boldsymbol{q})\dot{\boldsymbol{r}}_d \qquad (5)$$

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

4. PROBLEM OF FISH-CATCHING

To compare fishes' escaping intelligence and robot's catching one, we kept a procedure to catch a fish and release it immediately continuously for 30 minutes. 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.3, in which vertical axis represents the number of fishes caught in successive 5 minutes and horizontal axis represents the catching time. We had expected that the capturing operation would become easier as time passing on consideration that the fish may get tired. But to our astonishment, the number of fishes been caught decreased gradually.

The reason of decreased catching number may lie in the fishes' learning ability. For example, the fish can learn how to run away around the net as shown in Fig.4(a) by circular swimming motion with about constant velocity, having made a steady state position error that the net cannot reach to the chasing fish with even constant speed. Or fish can stay in the opposite corner against the net in the pool shown in Fig.4(b). And also, the fish can keep staying within the clearance between the edge of the pool
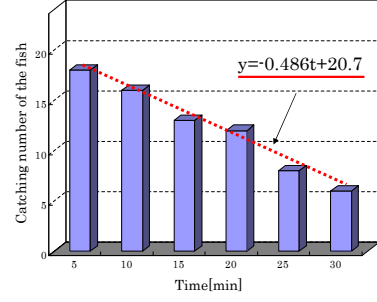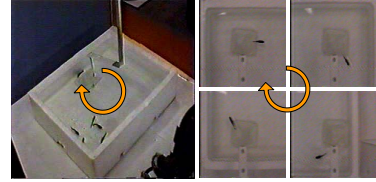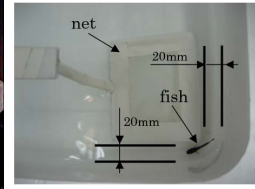

Fig. 3 Result of catching number

(a) Motion (1) of a fish

(b) Motion (2) of a fish   (c) Motion (3) of a fish
Fig. 4 Fish motion

and the net shown in Fig.4(c) where the net is inhibited to enter. To overcome these fishes' escaping intelligence, and to achieve more intelligent fish catching systems, we thought chaotic motion of the net with many 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. Then we propose Neural-Network-Differential-Equation to generate chaos as many as possible.

5. 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.3. The decreasing coefficient -0.486 represents adapting or learning velocity of the fishes as a group when the fishes' intelligence is compared with robot's catching. We named the coefficient as "*Fish's Intelligence Quotient*"(FIQ). 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 $\Delta\boldsymbol{r}_{chaos}^i$ in (4) effectively to exceed the fish intelligence.

6. 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 with periodic current stimulation being given 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 have 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. Whether the nerve cell of the organism excited by a stimulation signal seems to depend on nonlinearity of neurons' connection. Therefore, animal behavior and strategies can be evaluated from view point of chaos, and it may be applicable to fish catching.

There has been presented chaoses with a simplified model of Hodgkin-Huxley (H-H) model or BVP(Bonhoeffer-van der Pol) model. Using this BVP chaos model to produce unpredictable net motion we has been applied to fish-catching confirming the chaos has improved the robot's catching ability for a while thus it it could increase robot's intelligence. However often continuous catching/releasing experiment the fish finally has been able to ignore the chaos net motion. Therefore we thought single chaos model is not adequate to overcome fishes' escaping idea since the fishes change their behavior continuously. This is why we thought that plural or if possible as many chaos generators have to be prepared so the many chaos can go beyond the fishes' adapting intelligence.

7. 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 Neural-Network(N.N.) has been proven to have an ability to approximate any nonlinear functions with arbitrarily high accuracy[19],[20], 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 $\boldsymbol{f}(\boldsymbol{p}(t))$ as

$$\dot{\boldsymbol{p}}(t) = \boldsymbol{f}(\boldsymbol{p}(t)). \tag{6}$$

$\boldsymbol{p}(t) = [p_1(t), p_2(t), p_3(t)]^T$ is state variable. The nonlinear function of $\boldsymbol{f}(\boldsymbol{p}(t))$ in (6) is constituted by N.N.'s connections, which is exhibited in left part of Fig.5 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 equation, (6). We call it is Neural-Network-Differential-Equation.
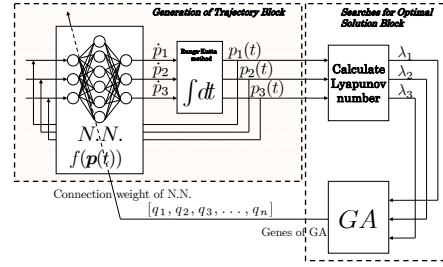

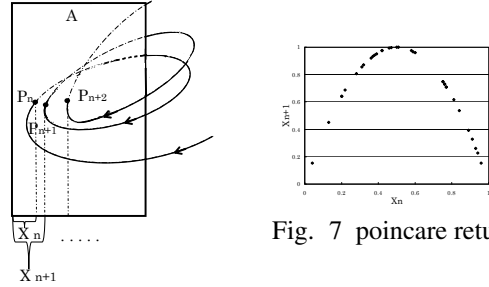Fig. 5 Block diagram of Chaos Generation

Fig. 6 Poincare section

Fig. 7 poincare return map

8. CHAOS VERIFICATION

Since there have been no simple criterion to determine whether an irregular oscillation 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.

8.1 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,
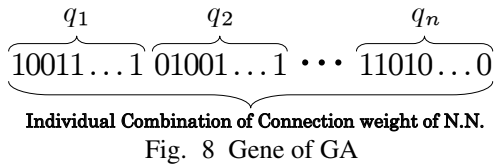
$$\lambda = \lim_{N \to \infty} \frac{1}{N} \sum_{i=0}^{N-1} \log |f'(x_i)|, \tag{7}$$

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

8.2 Poincare section

The trajectories of the motion made by neural-network-based nonlinear function (6) 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 an simple closed curve in three dimensions in Fig6. The plane "A" that intersects with this closed trajectory pointed by "P" is defined as the Poincare section.

The intersecting point 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.7. With the poincare return map of Fig.7 representing a shape of "Λ", the closed curve has the structure of stretching and folding. Looking at the left half of Fig.7, we can see the inclination coefficient $dx_{n+1}/dx_n > 1$

Fig. 8 Gene of GA

$$q_1 \quad q_2 \quad q_n$$

$$\overbrace{10011\ldots1}\ \overbrace{01001\ldots1}\ \cdots\ \overbrace{11010\ldots0}$$

Individual Combination of Connection weight of N.N.

and right half has $dx_{n+1}/dx_n < -1$, representing that left half has expansion and the other does contraction.

9. CHAOS GENERATE SYSTEM

Figure.5 represents a block diagram to find chaos by using GA and Lyapunov number. This GA is not used 1-Step GA described in Chapter 3 but used as a normal GA's procedure that evolves genes representing neural network coefficient's value. The trajectory $\boldsymbol{p}(t)$ in time domain obtained from Neural-Network-Differential-Equation is used for the calculation of Lyapunov number. Here, $\boldsymbol{L} = [\lambda_1, \lambda_2, \lambda_3]^T$ is a Lyapunov number, corresponding to state variables $\boldsymbol{p}(t) = [p_1(t), p_2(t), p_3(t)]^T$ in (6). Using this $\boldsymbol{L}$ for the evolution of GA, fitness function, g, is defined as follows,

$$g = k_1 \cdot \lambda_1 - k_2 \cdot |\lambda_2| - k_3 \cdot \lambda_3. \tag{8}$$

This fitness function incorporates 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 that time trajectory of (6) possibly 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 (8) appears to have relatively large positive value when $\lambda_1 > 0$, $\lambda_2 \approx 0$, $\lambda_3 < 0$, k_1, k_2, k_3 is positive coefficients. The gene of GA is defined as shown in Fig.8, with connection weights of N.N. being $\boldsymbol{q} = [q_1, q_2, \ldots, q_n]^T$. In this report we adopted a network of $3 \times 6 \times 3$ as shown in Fig.5, then the line number of connections and coefficient are 48, i.e., n=48. Because the gene is expressed in binary, converted to decimal and normalized into a range from 0 to 1. Then, generating a trajectory $\boldsymbol{p}(t)$ 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 $\boldsymbol{q}$ to have a highest value of g defined by (8), that means possible chaos trajectory.

10. VERIFICATION OF CHAOS

So far we have found four chaos patterns with different neural coefficients explored by GA mentioned in the previous section. We named them with a serial number as chaos01~chaos04. The followings are the introduction of those chaos about each individual character.
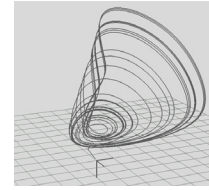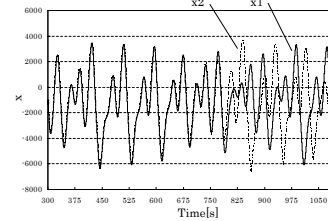

Fig. 9 Generated chaos trajectory 01

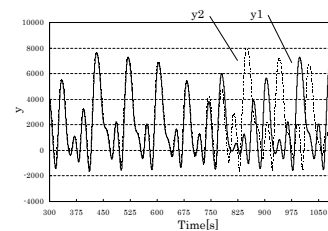Fig. 10 Generated trajectory 01 of x (300[s] to 1100[s])

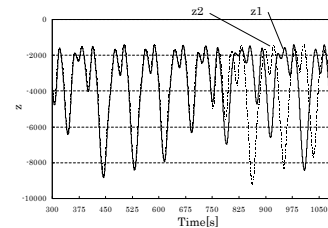Fig. 11 Generated trajectory 01 of y (300[s] to 1100[s])

Fig. 12 Generated trajectory 01 of z (300[s] to 1100[s])

10.1 Chaos01

10.1.1 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,$(+, 0, -)$.

10.1.2 Sensitivity to initial value

Two time-profile of trajectories with minutely different initial value are shown in Fig.10, Fig.11 and Fig.12. The trajectories of $(x_1(t), y_1(t), z_1(t))$ are the results 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.10 and y_1,y_2 are shown in Fig.11 and z_1,z_2 are shown in Fig.12.

We can see from Figs.10~12 that the two trajectories with minute difference of initial values divert often 800 seconds having passed, this mean the slight different initial values make large separation with each other, indicating sensitivity of initial value, which is one of the character of chaos.
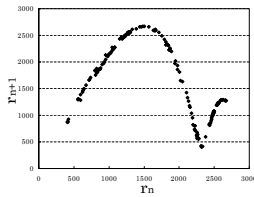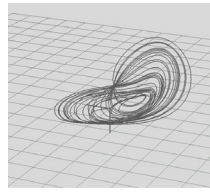
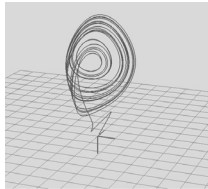Fig. 15 Generated chaos Fig. 16 Generated chaos
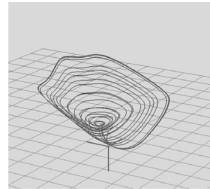trajectory 03   trajectory 04

10.1.3 Poincare return map

Chaos01's poincare return map is shown in Fig.13. One dimensional map can be seen in Fig.13, from which we can understand that the map represents expanding (left half of the Fig.13) and contracting (right half) that are essential character to happen to generate chaos.

Therefore, the chaos property of chaos01 is able to be confirmed from the viewpoint of Lyapunov number, an sensitivity of initial value, and the Poincare return map. It is similar from chaos 01 to chaos 04.

10.2 Chaos02∼Chaos04

Chaos02, Chaos03 and Chaos04 are shown in Fig.14, Fig.15 and Fig.16.

11. CONCLUSION

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 multiple chaos to make robot's intelligence overcome the fishes' one. 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 in the future.

REFERENCES

[1] R. Kelly, "Robust Asymptotically Stable Visual Servoing of Planar Robots", *IEEE Trans. Robot. Automat.*, vol.12, no.5, 1996, pp.759-766.

[2] P.Y. Oh, and P.K. Allen, "Visual servoing by partitioning degrees of freedom", *IEEE Trans. Robot. Automat.*, vol.17, pp.1-17, Feb.2001.

[3] T. Fukuda, and K. Shimojima, "Intelligent Control for Robotics", *Computational Intelligence*, 1995, pp.202-215.

[4] M. Bohlen, "A robot in a cage-exploring interactions between animals and robots", *CIRA.*, 1999, pp.214-219.

[5] Hee-Jun Park, Byung Kook Kim, Kye Young Lim, "measuring the machine intelligence quotient (MIQ) of human-machine cooperative systems", *IEEE Trans.*, vol.31, 2001, pp.89-96.

[6] M. Minami, H. Suzuki, J. Agbanhan, T. Asakura, "Visual Servoing to Fish and Catching Using Global/Local GA Search" *Int. Conf. on Advanced Intelligent Mechatronics*, Proc., 2001, pp.183-188.

[7] M. Minami, J. Agubanhan, and T. Asakura, "Manipulator Visual Servoing and Tracking of Fish using Genetic Algorithm", *Int. J. of Industrial Robot*, Vol.29, No.4, 1999, pp.278-289.

[8] H. Suzuki, M. Minami, J. Agbanhan, "Fish Catching by Robot Using Gazing GA Visual Servoing", *Transaction of the Japan Society of Mechanical Engineers*, C-68-668, pp.1198-1206, 2002 (in Japanese).

[9] Jun Hirao and Mamoru Minami: "Intelligence Comparison between Fish and Robot using Chaos and Random", *International Conference on Advanced Intelligent Mechatronics*, 2008, pp.552-557.

[10] K. Aihara, "Chaos in Neural System", pp.126-151, 1993 (in Japanese).

[11] R. FitzHugh, "Impulses and physiological states in theoretical models of nerve membrane", *Biophy.J.1*, pp.445-466, 1961.

[12] C. T. Lin and C. S. Lee, "Neural Fuzzy Systems", *Englewood Cliffs*, NJ:Prentice Hall PTR, 1996.

[13] Limin Peng and Peng-Yung Woo, "Neural-Fuzzy Control System for Robotic Manipulators", *IEEE Control Systems Magazine*, pp.53-63, 2002.

[14] M. Suzuki, "Evolutionary acquisition of complex behaviors through intelligent composite motion control", *Computational Intelligence in Robot. Automat. CIRA*, vol.27-30, 2005, pp.231-236.

[15] R. Endo, J. Hirao and M. Minami, "Intelligent Chaos Fish-Catching Based on Neural-Network-Differential-Equation", *SICE Annual Conference*, 2010, pp.1957-1962.

[16] William H. Press, Saul A. Teukolsky, William T. Vettering, Brian P. Flannery, "NUMERICAL RECIPES in C", *The Art Scientific Computing Second Edition*, 2002.

[17] M. Minami, J. Hirao, "Intelligence comparison between fish and robot using chaos and random", *Int. Conf. on Advanced Intelligent Mechatronics*, Proc., 2008, pp.552-557.

[18] Jun Hirao, Mamoru Minami ,Yasushi Mae and Jingyu Gao, "Emergence of Robotic Intelligence by Chaos for Catching Fish", *SICE Annual Conference 2007*, pp. 969-975, 2007.

[19] Limin Peng and Peng-Yung Woo, "Neural-Fuzzy Control System for Robotic Manipulators", *IEEE Control System Magazine February 2002*, pp. 53-63, 2002.

[20] C.T.Lin and C.S.Lee, "Neural Fuzzy System", Englewood Cliffs, NJ, Prentice Hall PTR, 1996.