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Intelligent Chaos Fish-Catching Based on Neural-Network-Differential-Equation

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***Abstract*—In this paper we tackle a Fish-Catching task under a visual feedback hand-eye system with catching net. As the time of tracking and catching process continues, and releasing the caught immediately into the same pool, then the fish can somewhat get accustomed to the net motion pattern and gradually find out new strategies on how to escape from the pursuing net. For the sake of such innate ability being widely existed in animal's behavior, the catching operation becomes tough and some effective intelligent method is needed to be conceived to go beyond the fishes' intelligence. The purpose of this paper is to construct intelligent system to exceed the fishes' intelligence in order to track and catch the fish successfully. Then we embed chaotic motion into the net motion of robot for better performance, and we have shown the chaotic net motion can overcome the fishes' escaping strategies.**

Keywords*—Neural Network, Chaos, emergence, Intelligent system, GA

I. 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 input information 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]. In our previous fish-catching research, the fish emotional behavior has also been examined and the robot with adaptive ability to react to the fish status is conceived. In our system, we have evaluated the intelligence degree of robots by the result of competition between fishes and the robot. We can examine the robot combined with chaos net motion is smarter than the fish to check that the robot can go beyond the fish by catching it successfully even after the fish finds out some escaping strategy. By evolutionary algorithms [6] Visual Servoing and Object Recognizing based on the input image from a video camera mounted on the manipulator has been studied in our laboratory [8], and we succeeded in catching a fish by a net attached at the hand of the manipulator based on the real-time visual recognition under the method of Gazing GA [9] to enhance the real-time searching ability. When tracking a swimming fish, we have learned that it is not effective for fish catching to simply pursue the escaping fish by visual servoing with velocity feedback control. In the actual problem the effective tracking became impossible because the fish can sometimes alter motion pattern suddenly under some emotional reasons of fear or the fish can take some strategy to try to get rid of the bothering net that keeps chasing it. The effective intelligent method is expected to be conceived in order to cope with the fish escaping strategy. While observing the fishes' adapting behavior to escape in the competitive relations with the robot, we found that we can define a "Fish's Intelligent Quotient"(FIQ) representing decreasing velocity of fish number caught by the net through continuous catching/releasing operation[7]. Through this measure we will compare the innate intelligence of the fish and the artificial intelligence of the robot. In this paper we adopt the chaos model generated by signal transfer in cell structure [11],[12]. We embed chaos into the Robot Dynamics in order to supplement the deficiency of our fish-catching system, because

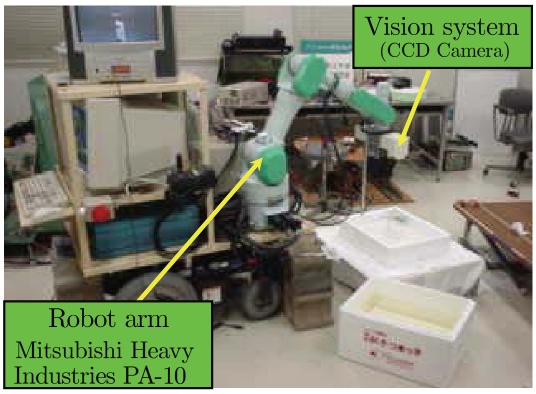


Fig. 1. Fish Catching system PA10

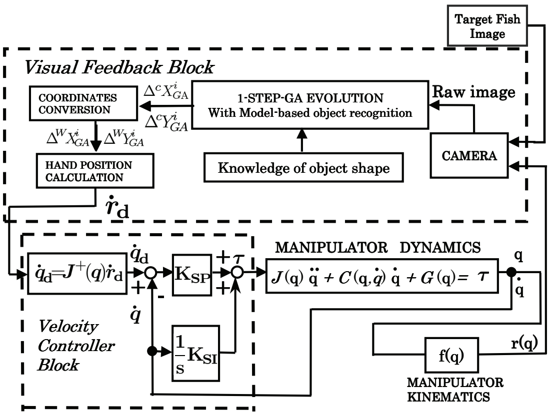


Fig. 2. Block diagram of the controller

intelligent composite motion control [13] becomes crucial in the catching fish process. The chaotic motion will be added to increase the fish catching according to the fish motion state and we can call that motion adaptive ability to fish intelligence[14]. We improved the system performance by the combination of N.N. prediction and chaotic motion to conceive a kind of idea with probabilistic chaotic motion, in other words we have tried a new strategy to make the system smart enough to exceed the fish intelligence.

II. Fish tracking and catching

The problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of $\boldsymbol{r}(t) = [x(t), y(t)]^T$ in order to maximize $F(\boldsymbol{r}(t))$, where $F(\boldsymbol{r}(t))$ represents correlation function of a new image and matching model to a fish at time t. $F(\boldsymbol{r}(t))$ is used as a fitness function of GA [9]. 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 is 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” [8]. 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 $\boldsymbol{r}(t)$ 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 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

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

where $\Delta\boldsymbol{r}^i$ denotes the servoing position error detected by 1-Step GA [8]. $\boldsymbol{K}_P$ and $\boldsymbol{K}_V$ given are positive definite matrix to determine PD gain. Now we add chaos items to (1) above, and we also need to redefine the meaning of $\dot{\boldsymbol{r}}_d^i$.

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

$$\Delta\boldsymbol{r}^i = k_1 \cdot \Delta\boldsymbol{r}^i_{fish} + k_2 \cdot \Delta\boldsymbol{r}^i_{chaos} \quad (2)$$

Here $\Delta\boldsymbol{r}^i_{fish} = \left[\ \Delta x^i_{fish} \quad \Delta y^i_{fish}\ \right]$, and $\Delta\boldsymbol{r}^i_{chaos} = \left[\ \Delta x^i_{chaos} \quad \Delta y^i_{chaos}\ \right]$., where $\Delta\boldsymbol{r}^i_{fish} = \Delta\boldsymbol{r}^i_{chaos}$ denotes a chaotic oscillation in $x - y$ plane. 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 do chaotic motion under certain condition satisfied either to lure the fish to come out of the corner or threaten the fish. 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

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

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.

III. 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 minutes experiment. 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 smoother as time passed 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 fish learning ability or emotional factor stated before. For example, the fish can learn how to run away around the net shown in Fig.4(a) by circular swimming motion with about constant velocity. The 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 and the net shown in Fig.4(c) 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, then we propose Neural-Network-Differential-Equation to generate chaos as many as possible.

IV. 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 $y = -2.286t + 20.2$ as shown in Fig.3. The decreasing coefficient

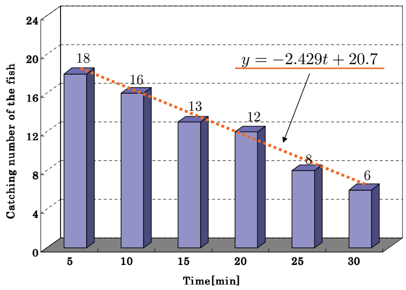
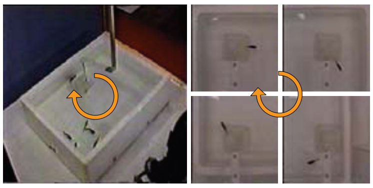
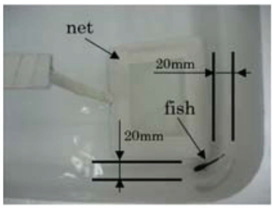


Fig. 3. Result of catching number



(a) Motion (1) of a fish

(b) Motion (2) of a fish



(c) Motion (3) of a fish

Fig. 4. Fish motion

-2.286 represents adapting or learning velocity of the fishes as a group when the fishes' intelligence is evaluated based on robotic performance given as a standard. We named the coefficient as "*Fish's Intelligence Quotient*"(FIQ). The larger minus value means high intelligence quotient, 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 $\Delta \boldsymbol{r}^i_{chaos}$ in (2) effectively to exceed the fish intelligence.

V. 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 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. 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

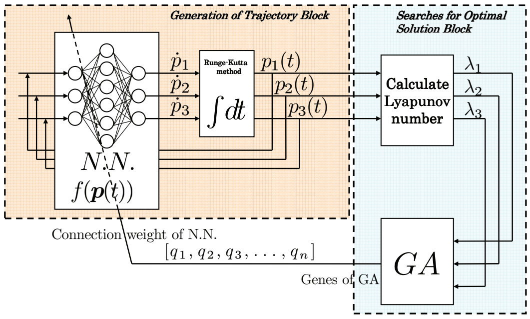


Fig. 5. Block diagram of Chaos Generation

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 Hodgkin-Huxley (H-H) 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 thoughtsingle chaos model is not adequate to overcome fishes' escaping idea since the fishes change their behavior continuously.

VI. Neural-network-differential-equation

For example, Lorenz and Rossler models is represented by a net of three differential equations, and known to have a chaotic attractor in phase space, producing three-dimensional chaotic trajectory. Since a Neural-Network(N.N.) has been proven to have an ability to represent any non-linear functions with the N.N. giving some conditions, we thought it is straightforward to make a differential equation including N.N. so that it can generate prural chaoses by changing N.N.'s coeficients. We define next nonlinear differential equation including N.N. function $f(\boldsymbol{p}(t))$ as

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

provided that $\boldsymbol{p}(t) = [p_1(t), p_2(t), p_3(t)]^T$ is input. We call that is Neural-Network-Differential-Equation. I show Eq.(4) in the block diagram in Fig.(5), Generation of Trajectory Block.

VII. Lyapunov exponent

As a character of chaos orbit, Lyapunov exponent expressed by the following equation is well known,

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

The extending and folding character are characters of chaos. So it is useful to measure with the computer.

VIII. Chaos generate system

Fig.5 is the block diagram to find chaos by using GA and Lyapunov number. This GA is not used 1-Step GA, described in Chapter II. Orbit 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. Using

$$\underbrace{\overbrace{10011\ldots1}^{q_1}\;\overbrace{01001\ldots1}^{q_2}\;\cdots\;\overbrace{11010\ldots0}^{q_n}}_{\textbf{Individual Combination of Connection weight of N.N.}}$$

Fig. 6. Gene of GA

this L for the evolution of GA, elitist preserve strategies, evaluation function is,

$$f = k_1 \cdot \lambda_1 - k_2 \cdot |\lambda_2| - k_3 \cdot \lambda_3. \tag{6}$$

This evaluation function has to consider the chaotic property of the Lyapunov spectrum. 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 $(+, 0, -)$. In parentheses indicate the sign of the Lyapunov spectrum. In other words, λ_1 is positive if f is a positive larger value, λ_2 is also positive or negative small values, λ_3 is negative case, f is set to be enlarged. In addititION $k_1,\ k_2,\ k_3$ is the coefficient of weight change. The gene of GA gives it like Fig.6, connection weights of N.N. $\boldsymbol{q} = [q_1, q_2, \ldots, q_n]^T$ to explore the GA that corresponds to each gene. Because the gene is expressed in binary, convert the decimal is used as connection weights and shrink the range from 0 to 1. Generated trajectory that using the connection weights determined Fig.5 of Generation of Trajectory Block. Then calculating Lyapunov number,and evolving the GA by evaluating function(6) are repeated. This procedure generates chaos by search by GA with a chaotic orbit that satisfies the Lyapunov spectrum.

IX. The proposed system

We generated two chaotic trajectories by nonlinear differential equations incorporated with Neural Network called α chaos and β chaos. These chaos orbit in three-dimensional representation are shown in Fig.8 and Fig.9. Within the dotted line part in Fig.7 representing proposed block diagram of fish-catching system with chaotic net motion, there are newly proposed chaos used to increase the net's motion varieties. When the preset conditions are satisfied, the chaos net motion will be combined into the Visual Servoing System. As mentioned before, when the fish motion is affected by emotional factor, the fish conceives new strategy to avoid being caught by net. Then reliable tracking and catching operation to overcome the fish's adaptive ability can become impossible without new machine adaptivity that goes beyond the fish's strategies. The proposed system flowchart in Fig.7 including a generator of chaos to make this system possess a kind of idea of tracking motion of the net by chaos.

X. Checking chaos

I confirm it about chaos generated by the above-mentioned system. We compare chaos $\alpha$and β that found in our laboratry to not chaos but famous trajectory. Lyapunov number of chaos α is Fig.10, and Fig.11, Fig.12, Fig.13 is trajectory of initial value $x_1(0) = 3.0, y_1(0) = 2.0, z_1(0) = 1.0,$

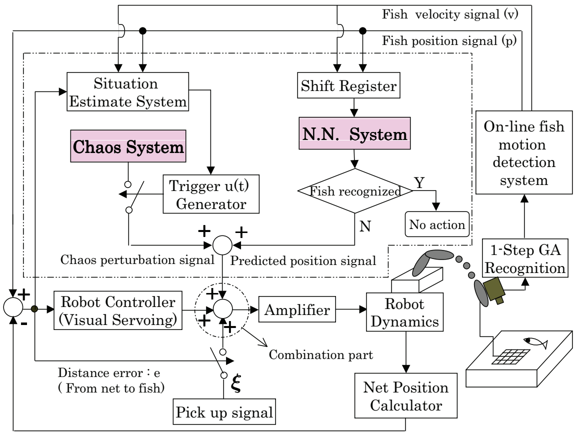
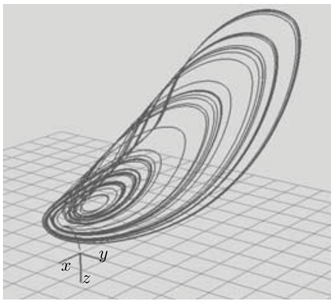


Fig. 7. The proposed system flow



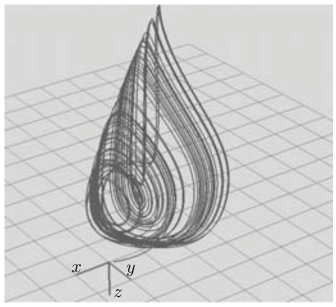


Fig. 8. Chaos α Trajectory

Fig. 9. Chaos β Trajectory

$x_2(0) = 3.001, y_2(0) = 2.001, z_2(0) = 1.001$. Lyapunov spectrum is $(+, 0, -)$. The two orbits are small errors gave $900[s]$ first time starting from the distances, it shows sensitivity to initial conditions.

Next, we confirm also β chaos orbit. Lyapunov number of chaos β is Fig.14, and Fig.15, Fig.16, Fig.17 is trajectory of initial value $x_1(0) = 3.0, y_1(0) = 2.0, z_1(0) = 1.0,\ x_2(0) = 3.001, y_2(0) = 2.001, z_2(0) = 1.001$. Lyapunov spectrum is $(+, 0, -)$. The two orbits are small errors gave $750[s]$ first time starting from the distances, it shows sensitivity to initial conditions.

Moreover,conpare two chaos orbit, outline of trajectory is completely different but lyapunov spectrum is similar.

XI. Compared orbit

For comparison, checked character also about the orbit which is not chaos. Fig.18 shows Limit cycle orbit that initial value $x = 1, y = 1, z = 2$, Fig.19 is expanded to track the initial value 1000 times $x = 1000, y = 1000, z = 2000$. Lyapunov number is Fig.22, individual orbit x,y,z is Fig.23, Fig.24, Fig.25. Two orbit gives a big difference of 1000 times, but it shows each track goes to the constant vibration. All lyapunov number is negative, and $\lambda3$ is particularly low.

Convergence orbit is Fig.20, Lyapunov number is Fig.26, ndividual orbit x,y,z is Fig.27. A trajectory which converges is opposite to the complexity of the chaotic trajectories to move. I showed a low value in the whole as expected.

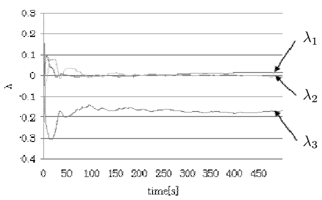


Fig. 10. lyapunovalpha

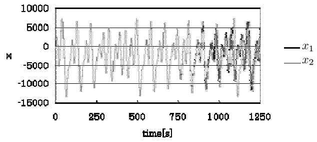


Fig. 11. alpha_x

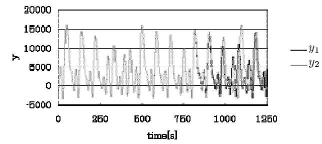


Fig. 12. alpha_y

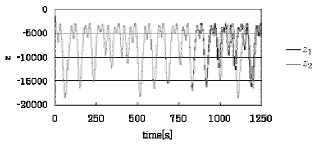


Fig. 13. alpha_z

Divergence orbit is 21, Lyapunov number is Fig.28, ndividual orbit x,y,z is Fig.29. It shows lyapunov number $\lambda1$, $\lambda3$ were also present indicating a slight positive, but $\lambda3$ shows very low value.

XII. Catching by servoing

We took a close observation into the fish tracking and catching experiments. This experiment, with net motion embedded with chaos, lasted for nearly $40s$ till the fish have gotten caught successfully. During the first $9s$, the net mounted at hand sometimes moved round the pool regularly to find out the swimming fish and chased the fish once it appears in the camera vision view. After $9s$ passed, the fish began to swim slowly along the edge of the pool where the net is forbidden to enter. The net's is preset to be coincided with the origin of the center of the image input from the camera looking down vertically to the pool and the net will be pulled up rapidly when the fish swims into the rectangular area 86×66[mm] located at the center of the net.

In order to check whether the new proposed fish-catching system is more effective than visual servoing catching depicted in Fig.3, we also kept catching 5 fishes in pool continuously under the same condition as the catching-fish experiment before. We recorded the catching number of fishes every 5 minutes. As analyzed before, the fish will generally get tired while being chased and caught and released continuously, in the meantime the fish will also get used to the net motion pattern. So, FIQ in Fig.3 is -2.429.

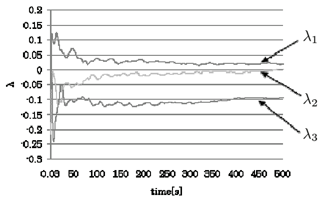


Fig. 14. lyapunovbeta

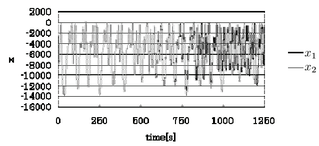


Fig. 15. beta_x

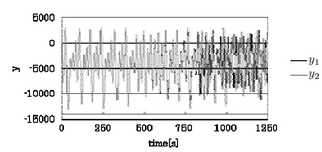


Fig. 16. beta_y

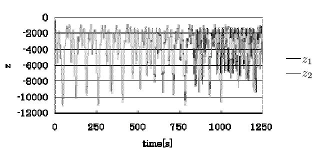


Fig. 17. beta_z

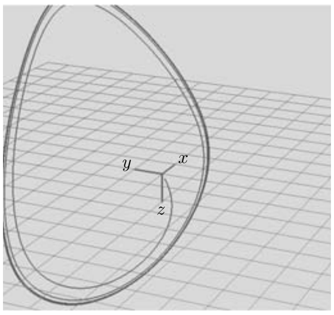


Fig. 18. LimitCycleA

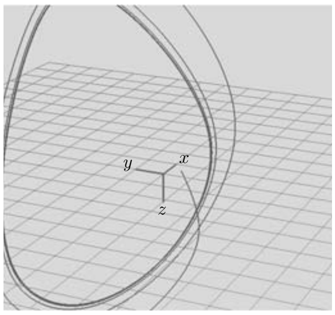


Fig. 19. LimitCycleB

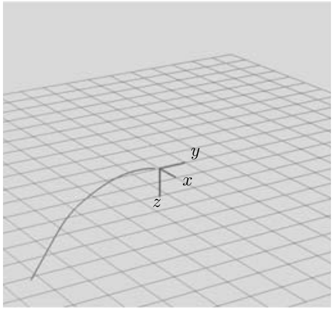


Fig. 20. convergence

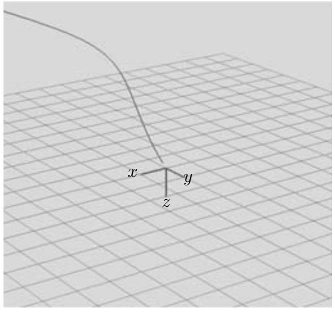


Fig. 21. divergence

XIII. Catching by chaos

Next, we conducted experiments using α chaos and β chaos. First, Fig.30 is the result of the experiment uses α chaos. FIQ is -1.0 in Fig.30. Second, Experimental results using β chaos shown in Fig.31. FIQ is 0.829 and that it has positive sign. Decreasing ratio in Fig.3, which is a catching result of visual servoing without chaos is -2.429, and this minus tendency express fish's intelligence being higher than the robot's one.

Here what we want to look into detail is the fish's behavior in 5 seconds before it has been caught, the fishs' swimming behavior can be the divided into 3 scenarios as follows:

(A) Fishes were caught while the net tracks the fish.

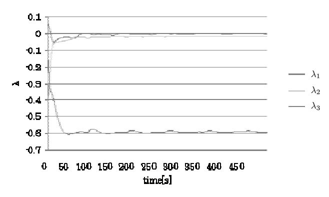


Fig. 22. LimitCycle

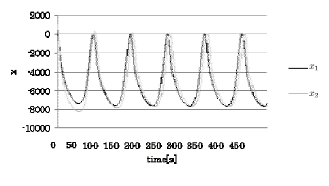


Fig. 23. LimitCycleOrbit_x

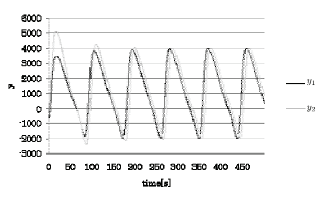


Fig. 24. LimitCycleOrbit_y

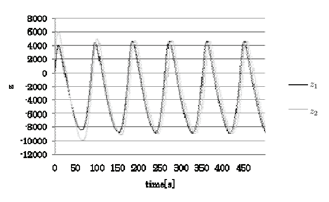


Fig. 25. LimitCycleOrbit_z

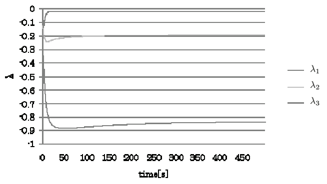


Fig. 26. lyapunovconvergence

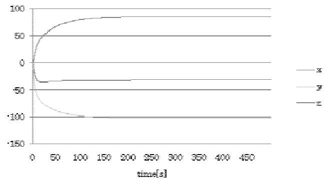


Fig. 27. convergence

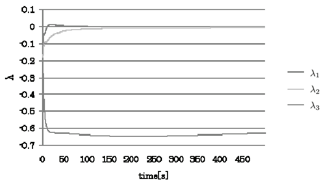


Fig. 28. lyapunovdivergence

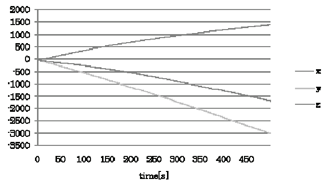


Fig. 29. divergence

(B) Fishes were caught when it happen to swim through above the net.

(C) When the camera happened to detect plural fishes in the image and that the servoing system happens to change the tracking fish to another one, the newly tracked fish was caught.

Above three fish's behavior before having been caught when α and β chaos have been used to catch, are examined and depicted as (A) to (C) in the figures of 30 and 31. In this way we can know how the fishes are caught. Fig.30 shows the experiment using α chaos. From the 5th to the 10th minute, the number of caught fishes in pattern (A) became zero, while total number of the fishes caught also decreased. From this, we can know the fishes became able to avoid the net driven by just visual servoing. Though fishes also can be caught in pattern (A) later, but we can see the tendency of decreasing of the number counted as pattern (A). In pattern (B) the number of caught fishes may be not stable, but the system could always catch fish in the 30 minutes by the scenario (B). This can the thought that it happens through the net's chaotic motion. In pattern (C), the changing of fish being tracked by the chaotic motion make a situation that the fishes are caught easily since the newly tracked fish might net aware of being targeted, triggered by the chaotic motion of the net. In other words, in pattern (B) and (C) the main reason why the fishes can be caught is the net's chaotic motion, so we can say the α chaos is effective to catch the fishes. In the experiment of β chaos, we used also 5 fishes in 30 minutes and got the number of the fishes caught in every 5 minutes as the some way before. The action in 5 seconds before the catching of the fish can be also divided into 3 patterns. The result is shown in Fig.31. From the result in Fig.31 FIQ is 0.829, in other words the motion of the net was beyond the fishes' intelligence. We can see that from the 5th to the 20th minute, the number of the fishes caught generally increased. This indicates fishes count exhibit their adaptability to the net's chaotic motion Looking in the details of the component of (A) to (C), (A) and (B) are increasing. Concerning (C) we can see the system can catch many fishes from the 20th to the 25th minute. We cannot find a clear tendency about the catching number of (C), showing

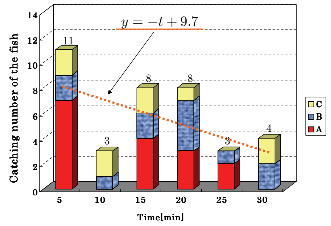


Fig. 30. Catching number of the fish with Chaos α

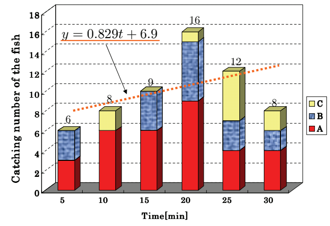


Fig. 31. Catching number of the fish with Chaos β

that the catching have been accidental and casual, which is happened when the fish being recognized was changed. In our opinion the reason why the decreasing tende ncy from 20th to 30th minutes against increasing from 5th to 20th can be understood that the fishes had noticed how to avoid from 20th to 30th.

XIV. Conclusion

We proposed a new method that chaos is embedded into the catching-net motion to cope with the fish learning ability trying to escape from the net. We suggested one more intelligent system than the traditional one in order to exceed the intelligence of the fish, and the effectivity of the system had been testified in real experiments.

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