2007 IEEE International Conference on
Robotics and Automation
Roma, Italy, 10-14 April 2007

Chaos-driving Robotic Intelligence for Catching Fish

Mamoru Minami, Gao Jingyu and Yasushi Mae

***Abstract*— We tackle a Fish-Catching task under a visual feedback hand-eye system with catching net. The fishes change escaping trajectory or speed up when being threatened as the net attached at hand approaches to them. Furthermore, as the time of tracking and catching process flows, the fish can somewhat get accustomed to the hand motion pattern and gradually find out new strategies on how to escape from the bothering net. For example, the fish can swim slowly along the pool edge where the net is forbidden to enter or keep a reasonable distance from the net as if it konws the visual servoing system bears steady state error by constant speed escaping. For the sake of such innate ability being widely existed in animal's behavior, the catching operation becomes tough and some effective intelligent method needs to be conceived to go beyond the fish's intelligence. The purpose of this research is to construct intelligent system to be able to exceed the fish's intelligence to survive. Then we embed chaotic motion into the hand motion of robot, and we have shown the chaotic net motion can overcome the fish escaping strategies.**

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] to improve dynamical behavior that differs from the classical AI has been applied intensively to the field of robotics. Typically, the animal world has been conceptual sources 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]. In these days, the technique about hierarchical organized control hardware and the multilevel multi-sensor based on fusion technique to obtain fused decisions has been described in [5]. 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. Behavior acquisition has been achieved and the simulated robot can learn to follow a light and to avoid hot dangerous objects shown in [7]. As known generally 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 [6].

This work was not supported by any organization

Mamoru Minami, Gao Jingyu and Yasushi Mae is with Graduate School of Engineering, Intelligent System, University of Fukui, Fukui city, Japan {minami, gao, mae}@rc.his.fukui-u.ac.jp

In our system, we will evaluate the intelligence degree by the result of competition between fishes and the robot. We can declare the system combined with chaos be smarter than the fish when the robot can overcome the fish's escaping strategy even after the fish finds out how to escape. As we did not find the research about the intelligence competition between animal and robot, we mainly dedicate ourselves to constructing a smart system that is more intelligent than the fish. So we not only employ the inspiration of animal behavior for robot intellectualization, we can also conceive a robot that can exceed the animal intelligence. By evolutionary algorithms [8] Visual Servoing and Object Recognizing based on the input image from a hand-eye camera has been studied in our laboratory [9], and we succeeded in catching a fish by a net attached at the hand based on the real-time visual recognition under the method of Gazing GA [10] 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 current fish by visual servoing with velocity feedback control. In the actual problem the effective tracking can be impossible because the fish can sometimes alter motion pattern suddenly under some emotional reasons of fear, or it can take some strategy to try to get rid of the bothering net that keeps chasing it. Those behaviors are thought to be caused by emotional factor and they can also be treated as a kind of innate intelligence though not in a high level. Based on the behavior observation in the real Fish-Catching experiment, the fish mostly swims stick to the pool edge for avoiding the net after being caught for a while. That is a serious problem for the Fish-Catching task because it is prohibited for the net to enter into the corner with a clearance of 2[cm] to avoid crashing to the pool wall. That shows the fishes have found the effective way to avoid being caught without wasting surviving power, so effective intelligent method is expected to be conceived in order to cope with the fish escaping strategy.

In this presentation we adopt the chaos model obtained from 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 intelligent composite motion control [13] becomes crucial in the catching fish process. The Chaotic motion is added to increase the possibility of catching fish according to the fish motion state, conceiving 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. The reasons to use chaos are first that it relates to biology and exists in process for life, secondly that the reproductivity

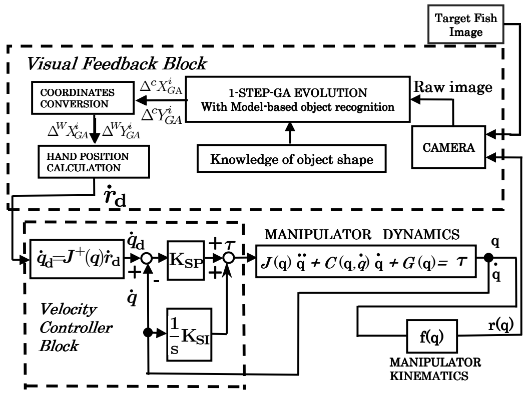


Fig. 1. Brock diagram of the control system

meaning that the chaotic random process can be represented explicitly and regenerated after it has been found that the trial process was effective, leads to remembering an effective idea that happens to be checked casually by chaos. Details will be given in the section of BVP Model.

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 $x(t), y(t), \theta(t)$ in order to maximize $F(\boldsymbol{\phi}(x(t), y(t), \theta(t)))$, where $\boldsymbol{\phi}(x(t), y(t), \theta(t))$ represents correlation function of a new image and matching model to a fish at time t. $F(\boldsymbol{\phi}(t))$ is used as a fitness function of GA. 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" [9]. 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 $\boldsymbol{\phi}(t)$ maximizing $F(\boldsymbol{\phi}(t))$ could be solved by "1-Step GA". We employed the combined method, which utilizes both the global search and the local search techniques of a GA, to perform a tracking and catching experiment of a swimming fish by using the experimental system depicted as a block diagram shown in Fig.1. The camera-to-fish distance is 450 [mm]. The size of the water pool is 300 (width)$\times$400 (length)$\times$100 (depth) [mm], and the net is 80$\times$100 [mm]. Catching the fish is executed by pulling up the net when the fish is within an area of 80$\times$60 [mm] at the center of the net attached at the robot hand and detected by a hand-eye CCD camera at the center of image view.

The aforementioned real-time recognition system using the shape of the fish as the knowledge base is depicted in the upper side of the block diagram in Fig.1. In the figure, $\boldsymbol{\Delta r} = [\Delta^W X^i_{GA}, \Delta^W Y^i_{GA}]^T$ is the X-Y deviation from the camera center to the fish expressed in the world coordinates, and the camera center also stands for the center of the catching net. The desired hand velocity at the i-th control period $\dot{\boldsymbol{r}}^i_d$ is calculated as

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

where $\Delta \boldsymbol{r}^i$ denotes the net current position vector from the camera center to the fish position observed in real time by 1-Step GA [9]. $\boldsymbol{K}_P$ and $\boldsymbol{K}_V$ given are positive definite matrix to determine PD gain. Now we add chaos to eq.(1), and we also need to redefine the meaning of $\dot{\boldsymbol{r}}^i_d$.

Here $\boldsymbol{r}^i_d$ designates the place robot hand should move towards. In order to determine the net destination, we think it is necessary to consider the fish motion state. Based on the fish current position, velocity and recognition result, two kinds of motion pattern can be taken and those are shown below. When the fish is recognized successfully, the net mounted at hand will chase the fish directly and $\Delta \boldsymbol{r}_{fish}$ denotes the recognized fish position deviation vector from the net center to the fish within the camera frame. When the fish stays in a corner of the pool, the net will do chaotic motion automatically and $\Delta \boldsymbol{r}_{chaos}$ denotes the vector towards the next point in chaotic trajectory. Therefore the new definition of $\Delta \boldsymbol{r}^i$ arisen in eq.(1) right side is shown as below:

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

Here $\Delta \boldsymbol{r}^i_{fish} = \begin{bmatrix} \Delta x^i_{fish} & \Delta y^i_{fish} \end{bmatrix}^T$, and $\Delta \boldsymbol{r}^i_{chaos} = \begin{bmatrix} \Delta x^i_{chaos} & \Delta y^i_{chaos} \end{bmatrix}^T$ that is obtained by solution of chaos differential equation in eq.(7) and a coefficient d. 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 the motion command signal to net is to track the fish. $k_1 = 0$ 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

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

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

$$\boldsymbol{\tau} = \boldsymbol{K}_{SP}(\dot{\boldsymbol{q}}_d - \dot{\boldsymbol{q}}) + \boldsymbol{K}_{SI} \int_0^t (\dot{\boldsymbol{q}}_d - \dot{\boldsymbol{q}}) dt \tag{4}$$

where $\dot{\boldsymbol{q}}_d - \dot{\boldsymbol{q}}$ is the velocity error of the joint angle, $\boldsymbol{K}_{SP}$ and $\boldsymbol{K}_{SI}$ are symmetric positive definite matrixes to determine PI gain. The orientation of the fish is measured in real time, but in the tracking and catching experiment, the measured orientation information is not used for the orientation control of the net as shown in the above equation. The manipulator servo update rate is 100[Hz].

In order to describe the details of the dynamical control flow, we show the intelligent motion control process in Fig.2. By 1-step GA recognition method [9], the fish position and

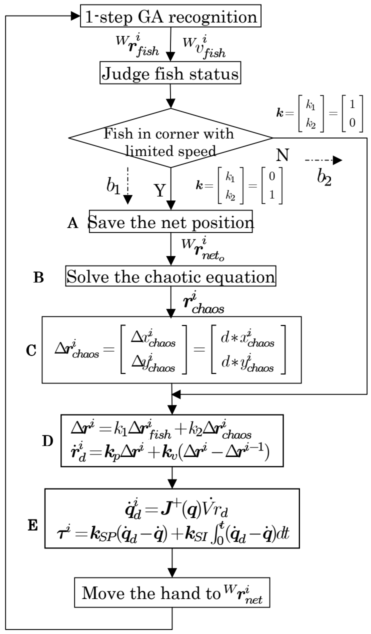


Fig. 2. Intelligent motion control process

velocity information can be available, with which the fish status can be judged in real time. When the condition of fish being in corner with a certain limited speed satisfied, the motion control process enters into b_1 branch with $k_1 = 0, k_2 = 1$, otherwise enters into b_2 branch with $k_1 = 1, k_2 = 0$, which determine the net motion type shown in Eq.(2). Before chaotic motion taken in b_1 branch, the current net position must be saved in advance for next net position calculation in Eq.(5):

$$ {}^W\boldsymbol{r}^i_{net} = \begin{bmatrix} {}^W x^i_{net} \\ {}^W y^i_{net} \end{bmatrix} = \begin{bmatrix} {}^W x^i_{net_o} \\ {}^W y^i_{net_o} \end{bmatrix} + \Delta \boldsymbol{r}^i \quad (5) $$

where the chaos equation Eq.(7) is solved shown in block B in accordance with the current time passing, so the used chaos solution is not repeated. Then we set the saved net position as the new origin of chaotic motion shown as ${}^W r^i_{net_o}$ in Eq.(5). The chaotic motion coordinate in camera frame is calculated as in block C, where d is a coefficient to adjust the chaos oscillation size with a value of 18 and can be regulated based on the vertical distance between camera and the pool. Then by the kinematics calculation process shown in block D and E, we can finally obtain each joint of the manipulator: $\boldsymbol{\tau}^i$. At last the hand is made to move to ${}^W\boldsymbol{r}^i_{net}$, which is the net position in world frame and can be calculated as follow:

III. Problem of fish-catching

In order to check the system reliability in real fish-catching experiment, we kept catching several fishes continuously for 35 minutes with steady condition of $k_1 = 1$ and $k_2 = 0$ shown in Eq.2 throughout the whole process. We released 8 fishes (with length 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 caught

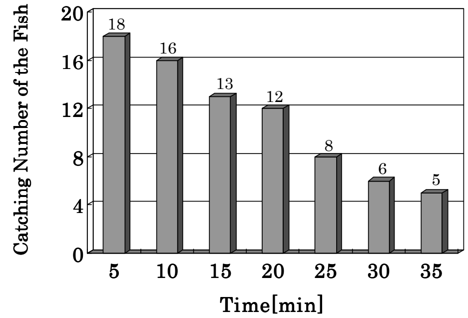
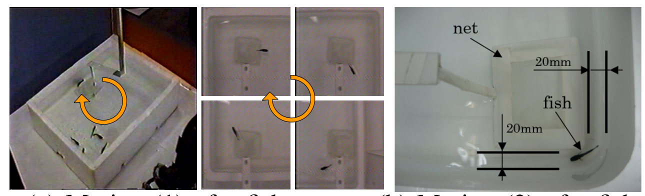


Fig. 3. Result of catching number



(a) Motion (1) of a fish (b) Motion (2) of a fish

Fig. 4. Fish motion pattern

fishes and horizontal axis represents the catching time. We had expected that the capturing operation would become smoother as time flew on consideration that the fishes may get tired and their swimming speed can slow down. To our astonishment, the Fish-Catching number 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 motion with about constant distance from the net. Also, the fish can keep swimming within the narrow strip area along the pool edge where it is prohibited for the net to enter shown in Fig.4(b). In order to solve the problem that may happen as above, more intelligent system needs to track and catch the fish effectively, in other words it comes to the problem on how to use the item $\boldsymbol{r}_{chaos}$ effectively to exceed the fish intelligence.

IV. The proposed system

In order to tackle the problem arisen in experiments stated in the previous section, we have proposed one new fish-catching system shown in Fig.5 to compensate the defects of the previous system. Within the dotted line part in Fig.5, there is one newly proposed Chaos System that are used to increase the intelligence degree of the whole system. When the preset conditions are satisfied, the chaos motion result will be combined and input into the Visual Servoing System. As mentioned before, when the fish motion is affected by emotional factor or the fish conceives new strategy to avoid being caught by net, reliable tracking and catching operation to overcome the fish adaptive ability can become impossible without new machine adaptation going beyond the fish strategies.

Let us pay attention to the details of the proposed system flowchart in Fig.5 including a generator of chaos to make this system possess a kind of idea of tracking motion of the net. The CCD camera acting as hand-eye is mounted on the manipulator and the block of 1-Step GA Recognition is

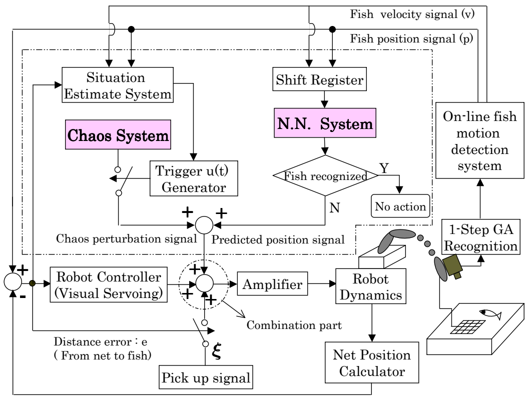


Fig. 5. The proposed system flow

used to perform recognizing the fish after hand-eye taking the image into the recognition block every 33ms. Then according to the recognized result, the next block called On-Line Fish Motion Detection System can deduce fish position and velocity information and after this there are two data channels that contain fish position and velocity signals respectively. The position and velocity signals flow into another branch in which there exists top block called Situation Estimate System used to estimate the fish motion state based on the value of position, velocity and distance error. In other words, that block is used to judge conditions like the fish speeding up suddenly, staying within a corner or keeping a constant distance against the net. Also in the same branch the Chaos System is used to generate chaos motion trajectory and Trigger $u(t)$ Generator is used to control the degree of chaos influence to the net motion. The data branch that only contains position signal is also used to regulate the net position by comparing its value with fish real position. Then the distance error can be obtained and it flows into Robot Controller that sends control signal to Amplifier. Finally, Robot Dynamics block performs manipulator motion control based on the inputting control signal.

V. BVP Model

In our research, we will embed chaos into the net motion to hold down the fish intelligence. Here we would like to show the reason why chaos is adopted for intelligence realization of robot. Firstly, the chaotic regulation relates to biology: Chaotic abnormal excitement are revealed in real experiment in 1982, where the vegetable cell and the nerve of mollusk had been periodically stimulated with electric current. Furthermore in 1984, the periodical electric current had also been exerted to the gigantic axon of squid and apparent chaotic response had also been obtained. In the later 1980s, some relationship existing between chaos and neural system had also been proved: In order to investigate the exciting pattern of sea cucumber motion nerve, Mpitosos research group have shown that the frequency fluctuation of the continuous discharge that has relationship with the motion rhythm is subjected to the chaotic regulation [11]. The phenomenon of chaotic motion can be frequently seen in living body. For example when you stare at one point still without blinking, it appears that your eyeballs have stopped

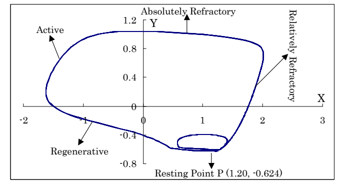


Fig. 6. Chaos trajectory

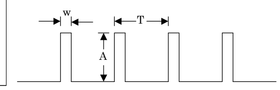


Fig. 7. The stimulus signal

motion somewhat, but in fact the eyeballs are still making an infinitesimal movement that is called chaotic vibration. Secondly chaos is reproductive random phenomenon: chaos time development never repeats past oscillation pattern, it means that it is random process. Regardless of this randomness the generating process could be represented simply with explicit mathematical formulation, and this leads to reproductivity of the time development by giving some initial conditions. We consider this reproductivity can be effective for robotic intelligence because robot control system can remember the chaotic process by memorizing a few conditions of the chaos generation such as the shape of equation and some initial conditions, this means the robot can remember what is the most effective process to overcome something confusing problem in a given dynamic environment after some chaotic behaviors have been tried. In contrast, pure random process like whitenoise does not have governing equation and it is a mathematical concept, then the time developing process could not be used afterward when it had been found that the past random process had some meaningfulness or effectiveness against the dynamic environment.

In order to clarify the existence of periodic response or chaotic response in the real mechanism of nerve membrane excitement, the analysis by use of Hodgkin-Huxley model has been performed. BVP model is a simplification of the Hodgkin-Huxley model and its differential equation is easy to solve in mathematics. Though the solution of the BVP model is not necessarily in complete coincidence with the real experiment data, the behavior of BVP equation has successfully regenerated the characteristics of the nerve membrane excitement in the qualitative analysis [11]. Based on the analysis above we make a trial to apply BVP model for mimicking the animal behavior in this research.

The BVP equation can be deduced from the following differential equation.

$$\ddot{x} + c(x^2 - 1)\dot{x} + x = 0 (c > 0) \tag{6}$$

Here $\dot{x}$ signifies the differential of x with respect to time. By some transformation, the full BVP model form can be finally acquired by adding a stimulus item z and the BVP equation is acquired as follow:

$$\begin{aligned} \dot{x} &= c(x - \frac{x^3}{3} + y + z) \\ \dot{y} &= -\frac{x + by - a}{c} \end{aligned} \tag{7}$$

here the solution x and y have the same meaning with x^i_{chaos} and y^i_{chaos} shown in block C in Fig.2, and $\Delta \boldsymbol{r}^i_{chaos} = \begin{bmatrix} d * x^i_{chaos} & d * y^i_{chaos} \end{bmatrix}^T$, which is given to eq.(2). Here we will give biological definition about x and y arisen from BVP differential equation. The item x denotes the value of reversal sign of membrane voltage in cell and y signifies the refractory nature. The item z denotes stimulus signal. Parameters a, b and c are confined as follow based on [12]:

$$1 - \frac{2b}{3} < a < 1, \;\; 0 < b < 1, \;\; b < c^2 \tag{8}$$

Fig.6 shows one example about the solution trajectory of BVP differential equation in x-y potential plane, and the nerve exciting process can also be obviously observed from this figure. In this chaotic locus, we adopt pulse signal as the stimulus. When proper stimulus signal shown in Fig.7 comes, nerve excitement can happen. The respond process will start from Resting Point P, then pass through Regenerative part, Active part, Absolutely Refractory part, then Relatively Refractory part, and finally return back to Resting Point P again. In other words, the responsive trajectory has such characteristic that although the nerve cell is in a state of stillness originally, it will get excited once accepting a proper instant pulse signal and return to the stationary state in the end. The coordinate of resting point P is (1.20,-0.624) as one characteristic of BVP solution.

In order to apply chaos to the current intelligent system appropriately, the relationship between chaotic response and stimulus need to be examined. One proposed method called Rungekutta that possess relatively optimal performance in solving differential equation has been adopted to the BVP differential equation solution procedure. Now we merely let parameters A and T in BVP equation vary with item W fixed to analyze the respond pattern. In the actual simulation by C program, if the amplitude A is strong enough and the T is long enough there will surely be a response once stimulus signal comes. On the contrary, if amplitude A is set weak enough or T short enough, there will not be any respond to stimulus no matter how frequent the stimulus comes. The response patterns with different A and T are shown in Fig.8 corresponding with Table 1 that includes parameters of stimulus signal and 4 responsive types.

TABLE 1

	A	T(ms)	W(ms)	type of response
(a)	- 0.8	100	3	2 stimulus : 1 response
(b)	- 0.91	100	3	5 stimulus : 4 responses
(c)	- 0.95	100	3	1 stimulus : 1 response
(d)	- 0.87	50	3	chaotic response

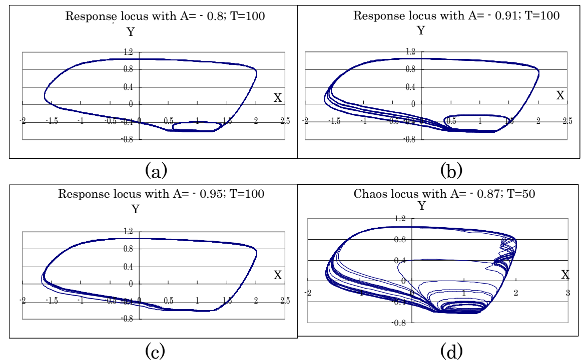


Fig. 8. The BVP response to stimulus

VI. Catching-fish experiment

In order to examine the new system, we have tried the Fish-Catching experiment and finally shown better Fish-Catching strategy can be created out against the fish escaping strategy. We try to imitate the animal judging pattern(mind) by chaos signal and it is considered that the time when the fish feels like getting out and the time when chaotic motion is taken can be matched, then the fish tends to be deceived that the scaring net is going further away and it can be caught by the net immediately once it swims out of the corner.

The following experiment was done in order to check the efficiency of chaos as an method for intelligence realization. We took a close observation into the fish tracking and catching experiment. This experiment, with net motion embedded with chaos, lasted for nearly $40s$ till the fish got 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 it is forbidden for the net to enter. In order to observe clearly how the chaotic motion would act effectively towards that kind of fish escape strategy, we had taken a series of pictures during the remaining 31s shown in Fig.9. The picture with $t = 9s$ shows the fish began to swim slowly along the pool edge. After judging the current situation that the fish swam stick to the pool edge, the net took chaotic motion during time interval from $t = 10s$ to $t = 31s$. The pictures from $t = 31s$ to $t = 36s$ show the process of the fish swimming out of corner and the visual servoing system lost the fish who exceeded the hand-eye view area when $t = 36s$. When the condition that the fish becomes out of the current camera vision area is satisfied, the net is designated to move towards the position that possibly be the next fish place after the fish got lost. So the fish fell into the vision span again and the net finally arrived at the place in front of the fish shown in picture with t=38s. The fish was finally caught at $t = 40s$ once it fell into the net range. The net is preset in the origin of this camera frame and it will be pulled up rapidly when the fish swims into the rectangular area 80×60[mm] round the net center.

In order to show the optimal performance with chaos adoption to the experimental system, we also took a series of pictures every $3s$ when we do not use chaotic motion and the fish swims stick to the pool edge slowly. From the Fig.10 we can see the net only followed the fish outside the prohibited area. No matter how much time flows, the fish still stayed within the thin strip area along the pool edge without daring to swim out. So the result is quite different from Fig.9 with chaos use and the catching operation ended with failure in Fig.10.

Fig.11(a) shows the x and y values of net trajectory in world frame Σ_W respectively versus time based on the data from experiment Fig.9. We can observe the net motion detail clearly within $40s$, and divide the net motion process into

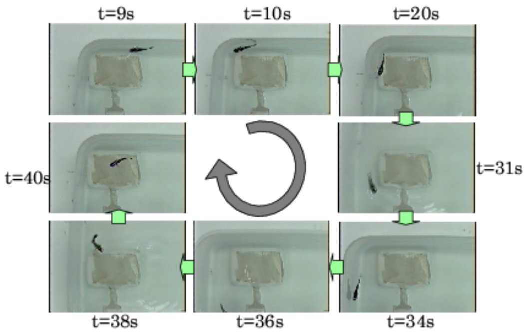


Fig. 9. The catching fish process by use of chaos

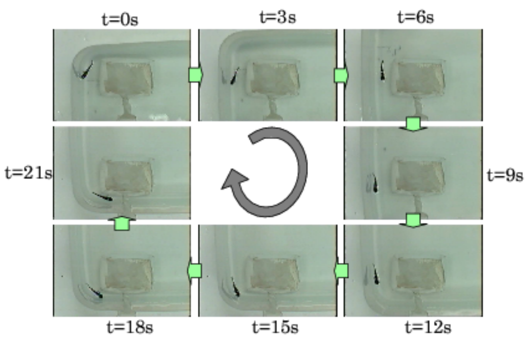


Fig. 10. The catching fish process without chaos

three stages p_1,p_2,p_3, which have different function to be stated later. Purely periodic chaos motion is fairly obvious between C_1 and C_2 in horizontal axis. E is the end point of net trajectory standing for the time when the net caught the fish successfully. For the intuitive convenience, we also show the net locus in x-y plane under Σ_W in Fig.11(b). In this figure, point $E(-143, 107)$ has the same meaning with point E shown in Fig.11(a). The net chaotic motion locus is drawn in the upper-left corner of (b). In chaotic trajectory we will treat resting point P shown in Fig.6 as the base point and make it always point to pool edge in real experiment for coincidence of the chaotic motion in each pool edge. For example, when the chaotic motion happened near the upside pool edge in this experiment, the chaotic trajectory became upside down like in Fig.11(b) that is different from the standard chaotic locus shown in Fig.6. The chaotic locus will also be cut off when chaos trajectory of the solution has exceeded the safe bound. In Fig.11(b), the left and above part of the chaos locus was cut off and restricted in the actual chaotic motion. The real net size is also drawn at the right side and the net center corresponds with the real net trajectory in the Fig.11(b).

Fig.12 shows the fish trajectory under world frame Σ_W in the real experiment. The shaded region represents the pool

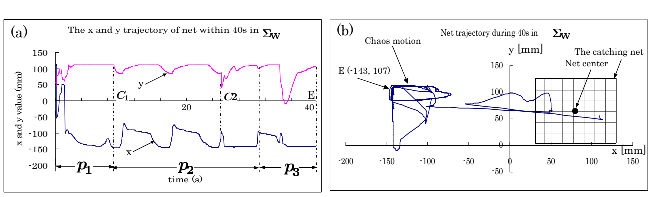


Fig. 11. Net trajectory in the experiment

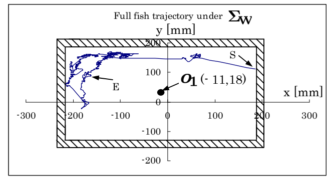


Fig. 12. Fish locus in world frame

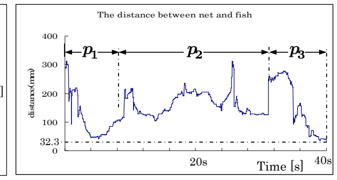


Fig. 13. Fish-to-net distance

edge from the top view. Within the pool, the fish swims around and is being chased by the net mounted at robot hand. The real pool size is about 400×300[mm], but we can also observe obviously that the data x and y have exceeded the limit size a little from the real experimental result. The reason lay on the offset error that is caused by the positional difference between pool center and origin of world frame Σ_W. When the two items above are not matched perfectly, the offset error can happen. In this experiment the new pool center is at $o_1(-11, 18)$ compared with the origin of world frame. The actual fish motion process starts from point S and ends at point E shown in Fig.12.

Fig.13 shows the distance between the fish and the net center. Considering the size of fish and net, we set the condition that when the fish has fallen into the range of 80×60[mm] from net center we can pull the net upwards promptly. We can see from the figure that the net is raised up and the fish is caught at $40s$ because the fish has fallen into the dangerous area of net ($32.3mm$ from the net center). Observing from the distance change in Fig.13 that describes the deviation from the net center to the fish we can also see when it enters into p_3 stage the distance between fish and net becomes larger suddenly. That phenomenon means the fish begins to speed up to swim out of the corner to avoid the scaring net, but unfortunately the net immediately chased it up and finally caught the fish successfully.

Fig.14 shows the fitness representing a correlation value used for calculating matching level of the fish in images with the model during 40s catching-fish experiment. Whether the fish is spotted or not is judged by the fitness value of 1-Step GA recognition and the fish can be considered recognized successfully if the fitness value was over 0.68.

In order to further check whether the new proposed fish-catching system is more effective than the original one, we also kept catching 8 fishes in pool continuously with the same condition as experiment in Fig.3. We recorded the fish-catching number with 5-minute span. As analyzed before, the fish will generally get tired while being continuously chased and caught, but the fishes became adaptive to the net motion pattern, so the fish-catching number kept decreasing in the former experiment shown in Fig.3. But after we

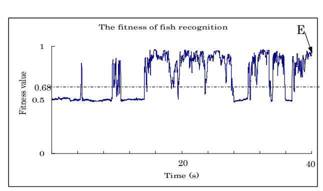


Fig. 14. Fish recognition fitness

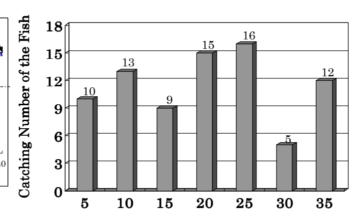


Fig. 15. Result of catching number

embedded the chaotic motion to net movement this time and the catching number of fish does not go down as shown in Fig.15. Although the fish-catching number is somewhat uncertain with time, the average number is about 11 and the decreasing tendency has stopped.

We used two different fish groups for two times' catching-and-releasing experiment shown in Fig.3 and Fig.15 respectively. The fish-catching number recorded every 5 minutes keeps decreasing with time flows in the first experiment, while the average fish-catching number can generally keep above a certain level in the second one. But we still doubt that whether it is the chaotic effect that prevents the fish-catching number decreasing because different fish groups may have different feature that affects the experiment result.

Now we tried another experiment with the same condition with the one in Fig.3 to examine whether the chaos adoption can prevent the decrease of the Fish-Catching number by using one 8-fish group that is different from the fishes used in former experiments shown in Fig.3 and Fig.15. The continuous catching-and-releasing operation lasts for 100 minutes, with mere visual servoing during the first 50 minutes and with chaos added in the remaining 50 minutes. The result is shown in Fig.16, in which the horizontal axis represents time and vertical axis represents the Fish-Catching number every 5 minutes. In order to observe the trend of Fish-Catching number, we adopt the linear Least-Squares approximation to fish-catching decreasing tendency, two linear functions can be generated as shown in Fig.16. In order to make it obvious to observe the trend of catching-number, we make separate analyses towards the two 50-minute periods. From the two approximated curve (denoted as n_1(t), n_2(t)) generated from Least-Squares method, we can see the Fish-catching number gradually decreased without chaotic motion used, but after 50-minute catching operation it can generally keep above the level of 11 fishes after chaos adoption. Altogether, the effectivity of chaotic motion embedded into the catching-net has been justified through the two experiments shown in Fig.15 and Fig.16 respectively from two different aspects. Therefore, the chaotic motion can supply the assurance to make the catching-fish operation go forward smoothly even the fishes think out some escaping strategies.

As the numerical analysis for the animal intelligence degree has so far not been performed, we want to make a trial give the numerical definition for animal intelligence. The inclination of n_1 corresponding with the tendency of

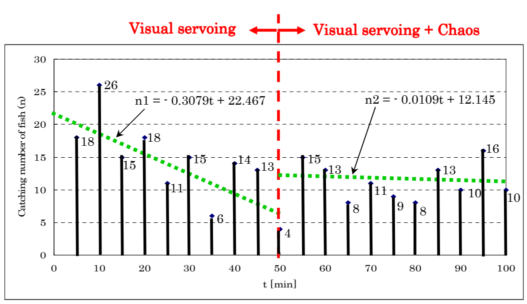


Fig. 16. Fish-Catching result in 100 minutes

fish catching-number during the first 50 minutes is -0.3079, and the inclination of n_2 coinciding with the remaining 50 minutes is -0.0109. In order to give a material description about the intelligence competition between robot and animals, we define the inclination as the Intelligence Degree Indicator (IDI) for the fish group on the condition that the fishes swimming in pool are chased and caught continuously by the catching net mounted at the robot hand. It is obvious that the smaller IDI value tends to be the higher intelligence level that the fish group can possess because the decrease in fish-catching number just shows that fishes have gradually become adaptive to the net. Furthermore, we consider the relationship between the robot and fishes can be figuratively described as the relationship between the predator and preys. The preys (fishes) can gradually generate adaptive ability (such as escaping strategies) to avoid the threatening predator (robot) for surviving because of the predator's continuous chasing and catching. From Fig.16, we can see the robot with chaotic motion used has effectively held down the fish learning ability in the longtime intelligence competition process between them because the IDI has varied from -0.3079 to -0.0109. Therefore the chaotic modification can overcome the fish intelligence and is useful for the contribution into the robotic intelligence realization.

VII. Conclusion

We propose a new method for intelligence realization by adopting chaos to cope with the the fish learning ability to escape from net. We suggest one more intelligent system than the traditional one in order to exceed the fish ingelligence and the effectivity of the system is testified in real experiments.

References

[1] R. Kelly, "Robust Asymptotically Stable Visual Servoing of Planar Robots", *IEEE Trans.*, 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, Feb.2001, pp 1-17.

[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] R.C. Luo, S.H.H. Phang, K.L. Su, "Multilevel multisensor based decision fusion for intelligent animal robot", *ICRA.*, vol.4, 2001, pp 3294-3299.

[6] 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.

[7] M. Dorigo, U. Schnepf, "genetics-based machine learning and behavior-based robotics: a new synthesis", *IEEE Trans.*, vol.23, 1993, pp 141-154.

[8] 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.

[9] 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.

[10] H. Suzuki, M. Minami, "Visual Servoing to catch fish Using Global/local GA Search", *IEEE/ASME Transactions on Mechatronics*, Vol.10, Issue 3, 2005.6, pp 352-357.

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

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

[13] 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.