# Fish Catching Experiments to Overcome Fish's Intelligence by Visual and Prediction Servoing in combination with Chaos and Random Motions

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**Abstract:** In our laboratory, to make the intelligent robot, we executed fish's catch experiment by a robot, and compared the intelligence of both : robot's catching ability and fish's escaping ability. When experimenting repeatedly on catching and releasing, the fish began to generate evasive actions, for example staying at corners of the pool in which the fish swims. We tried to catch the fish using some strategies such as prediction servoing, chaos orbits and random motions to overcome the fish's escaping strategies. In this paper, we used visual servoing and prediction servoing in combinations with chaos orbits and random motions of the net. We have compared the number of captured fish—the relative intelligence quotient of the fish by comparing with robot and evasive action. Then we have confirmed the effective strategies, and evaluated the results we have experimented this time.

Keywords: Visual servoing, Chaos, Intelligence, Fish

# **1. INTRODUCTION**

In recent years, visual tracking and servoing in which visual information is used to direct the end-effector of a manipulator toward a target object has been studied in some researches [1], [2]. A new trend of machine intelligence [3] that differs from the classical AI has been applied intensively to the field of robotics and other research areas like intelligent control system. Typically, the animal world has been used conceptually by robotics researcher 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.

In our system, we will evaluate the intelligence degree between fish and the robot by Fish-Catching operation. We can declare that the fish-catching system combined with chaotic net motion be smarter than the fish when the robot can beat the fish's intelligence by catching it continuously and successfully even after the fish finds out some escaping strategy. As we did not find the research about the intelligence comparison between animal and robot, we mainly dedicate ourselves to constructing a smart system that is more intelligent than the fish. We consider that the competitive relation can be very meaningful as one way to discuss robotic intelligence. So we not only employ the inspiration of animal behavior for robot intellectualization, we can also conceive a robot that can exceed the animal's intelligence. By evolutionary algorithms, 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), and we succeeded in catching a fish by a net attached at the hand of the manipulator based on the real-time visual recognition



Fig. 1 Experimental system

under the method of Gazing GA to enhance the real-time searching ability.

By evolutionary algorithms [5], 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) [6], 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 [7], [8] to enhance the real-time searching ability.

We have learned that it is not effective for fish catching to simply pursue the escaping fish by visual servoing with velocity feedback control. Actually, the effective tracking can be 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. Those behaviors are thought to be caused by emotional factors and they can also be treated as a kind of innate fish intelligence, even though not in a high level. Based on the fish behavior observation in the real Fish-Catching experiment, the fish mostly swims stick to the pool edge for avoiding the net after being caught several times. That fish's behavior is a serious problem for the Fish-Catching task because when the fish only stay at the corner where the robot's net attached at hand is prohibited to enter the corner in Fish-Catching operation for avoiding the net crashing against pool walls. That shows the robot system is not intelligent enough, so effective method is expected to be conceived in order to cope with the fish's escaping strategy. While observing the fish's adapting behavior to escape in the competitive relations with the robot, 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, which stand for the fish's learning velocity. Through this measure we will compare the innate intelligence of the fish and the artificial intelligence of the robot.

In this paper we explain about the fish catching method and evaluation index in section 2, how to make chaos and how is the chaos implemented into net motions in section 3, fish catching experiments in section 4, followed by conclusion in section 5.

# 2. FISH CATCHING SYSTEM

#### 2.1 On-line Tracking

Consider the 2-D raw-image of a target fish shown in Fig.2(a), its corresponding 3-D plot is shown in Fig.2(b). In this figure(b), the vertical axis represents the image brightness values, and the horizontal axis, the image plane. To search for such a target fish in the raw-image, a geometrical triangular shape of the surface-strips model as shown in Fig.3(a) is used. Let us denote the inside surface of the model as  $S_{ss1}$  and the contour-strips as  $S_{ss2}$ . Also, the combination is designated as  $S_{ss}$ . When the position and orientation of surface-strips model  $S_{ss}$ is defined as  $\phi(t) = [x(t), y(t), \theta(t)]^T$ , which designates the position and orientation of the origin of the model, then  $S_{ss}$  moves in the camera frame and a set of x-y coordinates of the moving model is expressed as  $S_{ss}(\phi)$ . Then the brightness distribution of raw-image corresponding to the area of the moving model is expressed as  $p(\tilde{r}_{i,j}), \tilde{r}_{i,j} \in S_{ss}(\phi)$ , then the evaluation function  $F_{ss}(\phi)$  of the moving surface-strips model is given by Eq.(1).

$$F_{ss}(\boldsymbol{\phi}(t)) = \sum_{\boldsymbol{\tilde{r}}_{i,j} \in S_{ss1}(\boldsymbol{\phi}(t))} p(\boldsymbol{\tilde{r}}_{i,j}) - \sum_{\boldsymbol{\tilde{r}}_{i,j} \in S_{ss2}(\boldsymbol{\phi}(t))} p(\boldsymbol{\tilde{r}}_{i,j})$$
(1)

This expression means the integrated brightness difference between the one of the internal surface and the one of the contour-strips of the surface-strips model. The filtering result of the surface-strips model-based function of Eq.(1) with respect to Fig.2(a) is shown in Fig.3(b). We can see the filtering result has a peak corresponding to the position of the target fish in the raw-image. An evaluation using the surface-strips model means that  $F_{ss}(\phi(t))$  takes into account the integration and differentiation of the object signal and the background noise simultaneously, and we can see this character is effective for such noisy image as shown in Fig.2(a). Actually we cannot get always the highest peek in the filtered image



(a)Surface-strips model (b) $F_{ss}(\phi)$ Fig. 3 Surface-strips Model to search a fish

at the position of the target object, but we can set such an environment that the highest value of  $F_{ss}(\phi(t))$  is obtained only if  $S_{ss1}$  fits to the target object being imaged.

As the result of above discussion the problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of  $\phi(t)$  such that maximizes  $F_{ss}(\phi(t))$ .  $F_{ss}(\phi(t))$  is used as a fitness function of Genetic Algorithm (GA) to recognize a target in a dynamic image input by video rate, 33 [fps]. The online tracking system must have real-time nature, that is, the searching model must converge to the fish in the successively input dynamic images. An evolutionary recognition process for dynamic images is realized by such method whose model-based matching by evolving process in GA be applied at least only one time to one raw image input successively by video rate. We named it as "1-step GA,"[6]. When the converging speed of the model to the target in the dynamic images should be faster than the swimming speed of the fish, then the position indicated by the highest gene represents the fish's position in real-time. We have confirmed that the above timevariant optimization problem to solve  $\phi(t)$  maximizing  $F_{ss}(\boldsymbol{\phi}(t))$  could be solved by "1-step GA."

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#### 2.2 Chaos

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

The desired hand velocity at the *i*-th control period  $\dot{r}_{d}^{i}$ 



Fig. 4 Result of catching number

is calculated as

$$\dot{\boldsymbol{r}}_{d}^{i} = \boldsymbol{K}_{P} \Delta \boldsymbol{r}^{i} + \boldsymbol{K}_{V} (\Delta \boldsymbol{r}^{i} - \Delta \boldsymbol{r}^{i-1})$$
(2)

where  $\Delta r^i$  denotes the servoing position error detected by 1-Step GA [6].  $K_P$  and  $K_V$  given are positive definite matrix to determine PD gain. Now we add chaos items to (2) above, and we also need to redefine the meaning of  $\dot{r}_d^i$ . The simple PD servo control method given by (2) is modulated to combine a visual servoing and chaos net motion by redefinding  $\Delta r^i$  as,

$$\Delta \boldsymbol{r}^{i} = k_{1} \cdot \Delta \boldsymbol{r}^{i}_{fish} + k_{2} \cdot \Delta \boldsymbol{r}^{i}_{chaos} \tag{3}$$

Here  $\Delta r_{fish}^{i} = \left[ \Delta x_{fish}^{i}, \Delta y_{fish}^{i} \right]$  is the tracking error of fish from the center of camera frame, and  $\Delta r_{chaos}^{i} = \left[ \Delta x_{chaos}^{i}, \Delta y_{chaos}^{i} \right]$  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 pure visual servoing, and  $k_{1} = 0$  and  $k_{2} = 1$  indicate the net will track chaotic trajectory made by Neural-Network-Differential-Equation(NNDE) being explained later in this paper. The desired joint variable  $\dot{q}_{d}$  is determined by inverse kinematics based on  $\dot{r}_{d}$  by using the Jacobian matrix J(q), and is expressed by

$$\dot{\boldsymbol{q}}_d = \boldsymbol{J}^+(\boldsymbol{q})\dot{\boldsymbol{r}}_d \tag{4}$$

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

#### 2.3 Random motions

The deformed random trajectories x(t), y(t) are used to define  $\Delta r_{random}^{i}$  as  $\Delta r_{random}^{i} = \begin{bmatrix} x(t), y(t) \end{bmatrix}$  and by replacing a eq.(3) as follows, random is used on the same conditions as the time of chaos [9].

$$\Delta \boldsymbol{r}^{i} = k_{1} \cdot \Delta \boldsymbol{r}^{i}_{fish} + k_{2} \cdot \Delta \boldsymbol{r}^{i}_{random}$$
<sup>(5)</sup>

#### 2.4 Prediction servoing

This way act predicting T[s] after, and tracking future position of fish. We replaced  $\Delta r^i$  as

$$\Delta \boldsymbol{r}^{i} = \hat{\boldsymbol{r}}(t + \Delta T). \tag{6}$$

In this experiment, the time is to predict the future position in 0.48[s] [10].

#### 2.5 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 ??, which exhibit the number of fish caught by the robot in five minutes, on condition of the caught fish released into the same pool immediately. The decreasing coefficient -0.486 represents adapting or learning velocity of the fishes as a group when the fish's intelligence is compared with robot's catching ability. We named the coefficient as "Fish's Intelligence Quotient" (FIQ), since the decreasing tendency that is the value of coefficient can represent the fish's learning velocity to conceive a new escaping strategies-stay at the corner or swim with constant speed on a circle trajectory. The larger minus value of FIQ 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  $\Delta r^i_{chaos}$  in (3) effectively to exceed the fish intelligence.

## **3. ORIGINAL CHAOS**

#### 3.1 Validity of chaos

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.

#### **3.2** The chaos model used in the experiment

Figure 6 shows the chaos model used in the experiment. The chaos model was generated by the system given by Fig.6 using Neural-Network-Differential-Equation[11] in our laboratory. We define next nonlinear differential equation including N.N. function f(p(t)) as

$$\dot{\boldsymbol{p}}(t) = \boldsymbol{f}(\boldsymbol{p}(t)). \tag{7}$$

 $p(t) = [p_1(t), p_2(t), p_3(t)]^T$  is state variable. The nonlinear function of f(p(t)) in (7) is constituted by N.N.'s connections, which is exhibited in left part of Fig.6 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, (7).

### 4. FISH CATCHING EXPERIMENT

#### 4.1 Problem of fish-catching

To compare fish's escaping intelligence and robot's catching one, we kept a procedure that is catching a fish



Fig. 5 Chaos model



Fig. 6 Block diagram of Chaos Generation

and releasing it immediately continuously for 30 minutes. 5 fishes (size is about 40[mm]) are released in the pool in advance, and once the fish was gotten, it would be released to the same pool at once. The result of this experiment is shown in Fig.5, in which vertical axis represents the number of fish 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 fish caught decreased gradually. The reason of decreased catching number may lie in the fish's learning ability. For example, the fish can learn how to run away around the net as shown in Fig.7 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. This steady state error between the net and the fish inevitably appears by fish's swimming with constant speed, since the robot's net is driver by PD controller given by (2)-control theory suggests that PD controller and ramp position input (equal to constant velocity) made steady state error. Or the fish can keep staying within the clearance between the edge of the pool and the net shown in Fig.8 where the net is inhibited to enter. To overcome these fish's 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 fish's escaping intelligence, since huge variety of chaos trajectories seems to be unpredictable for the fish to adapt them.

## 4.2 Fish catching experiment

We did four fish catching experiments  $1 \sim 4$  listed as below. According to the experiments, prediction servoing can be used to shorten the distance between the net and fish, and chaos can be used to lure fish out from corner.

- 1. Visual servoing
- 2. Prediction servoing
- 3. Chaos
- 4. Random motions

The validity of the prediction servoing is tested by comparing the experiment 1 with the experiment 2. In the same way, the validity of the chaos is tested by comparing the experiment 1 with the experiment 3. The experiment 3 was done in two ways by experienced fish and inexperienced fish.

# 4.3 Catching action and fish's escaping strategy

Catching actions were classified into pattern (A) and (B). And fish's escaping strategies were classified into pattern (C) and (D). The patterns from (A) to (D) were shown as below.

- (A) Catching fish which swim at center
- (B) Catching fish which was in corner
- (C) Circular swimming motion(Fig.7)
- (D) Keep staying at corner(Fig.8)



Fig. 7 Circular swimming / escaping motion



Fig. 8 Keeping stationary at corner

# 4.4 Environment of experiments

- 1. Experiment environment is shown below.
- 2. The kind of fish : Black Molly
- 3. The pool size : 330  $\times$  420mm
- 4. Height from a bottom to the water surface : 60mm
- 5. Water temperature was set as 30 . If water temperature is low, fish will weaken.
- 6. Experiment time is set as 30 minutes.
- 7. Five fish are used in one experiment.
- 8. If several fish are captured at one time, it counts as one.

# 4.5 Results of experiment

4.5.1 Fish catching with visual servoing

Visual servoing is only used in this experiment. The result is shown as Fig.9 and Fig.10.

As shown in Fig.9, the number of caught fish is decreasing with time because fish learned how to escape. The ratio of the pattern (C) is decreasing gradually and pattern (D) is increasing as shown in Fig.10. Fish learned that the escaping action pattern (D) is safer than (C). Fish judged safety position, because the motion of the robot stops at the corners. FIQ shows the negative value, namely the intelligence of the fish exceeded that of robot.

# 4.5.2 Fish catching with prediction servoing

It is the experiment of prediction servoing. The result is shown as Fig.11 and Fig.12.

Fish can be caught more by prediction servoing than by visual servoing, as shown in Fig.11. Prediction servoing contacts the distance of the net and fish. It is effective to the fish's escaping action pattern (C). The ratio of the pattern (C) changes to (D) as shown in Fig.12. Prediction servoing became invalid with the end of the experiment.

#### 4.5.3 Fish catching with chaos

It is the experiment of visual servoing added chaos model. First, experiment was did with fish, which experienced visual servoing. The result is shown as Fig.13 and Fig.14. The fish learned keep staying in the corners in the last experiment only visual servoing. The robot could not catch the fish with the end of the last experiment. But the robot added chaos could catch the fish from the beginning of the experiment to the final stage. All the catching action were pattern (B). The effect was checked that chaos can lure fish from the corners. FIQ shows the positive value, namely the intelligence of the robot exceeded that of fish.

Second, we experimented on the fish which inexperienced visual servoing. The result is shown as Fig.15 and Fig.16. The fish mainly acted of the escaping action pattern (D). Catching by chaos pattern (B), which is effective in pattern (D) was few, and pattern (A) was increasing. The reason considered, there was a possibility that fatigue of the fish were related. FIQ shows the positive value, namely the intelligence of the robot exceeded that of fish.

#### 4.5.4 Fish catching with random motions

It is the experiment of visual servoing added random motions. The result is shown as Fig.17 and Fig.18. The escaping action (D) increased gradually. It has checked the random motions cannot excite and lure the fish. FIQ shows the negative value, namely the intelligence of the fish exceeded the robot's. A conclusion was that chaos was more effective than the random motions against escaping action (D).

# **5. CONCLUSION**

By this research, we experimented using visual servoing, prediction servoing, chaos and random motions, and compared them. Prediction servoing and chaos model ware effective against fish's escaping actions. In our laboratory, we succeeded in generation of the plural chaos orbits. It is desirable to conduct the experiment using several chaos models in the future.



Fig. 9 Caught fish number by using visual servoing with fish not having experienced catching operations



Fig. 10 Ratio of fish's escaping actions by using visual servoing with fish not having experienced catching operations



Fig. 11 Catching number of fish by using prediction servoing with fish not having experienced catching operations



Fig. 12 Ratio of fish's escaping actions by using prediction servoing with fish not having experienced catching operations

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Fig. 13 Caught fish number by using chaos with fish having experienced catching operations



Fig. 14 Ratio of fish's escaping actions by using chaos with fish having experienced catching operations



Fig. 15 Caught fish number by using chaos with fish not having experienced catching operations



Fig. 16 Ratio of fish's escaping actions by using chaos with fish not having experienced catching operations



Fig. 17 Caught fish number by using random with fish not having experienced catching operations

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Fig. 18 Ratio of fish's escaping actions by using random with fish not having experienced catching operations

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