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Reduction of Fish's Learning Speed by Chaos and Randomness in Antagonistic Relationship of Robot and Fish

Keita Mori, Mamoru Minami and Akira Yanou

Abstract— **In this paper, we report relative comparison on leaning speed of fish in an antagonistic relation of prey and predator—the prey is a fish and the predator is a robot seeking to catch the fish by a net attached robot's hand through visual servoing. It was confirmed that the fish have found escaping strategy by itself, e.g., staying at corners of a pool where the net is inhibited from closely approaching to the corners to avoid the net clashing to the pool wall. The effectiveness of the conceived escaping strategies by fish have been measured as learning speed that describe decreasing tendency of how many fish could be caught in constant time when the fish caught being released immediately to the same pool. To overcome such fish's ability to conceive new strategies for escape, in this paper, chaos and randomness have been added to the net motion, where some experiments are conducted to examine whether chaos and randomness can decrease the fish's learning speed.**

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 re- search 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.

D.Wechsler said " Intelligence is the aggregate or global capacity of the individual to act purposefully, to think rationally and to deal effectively with his environment [5]. " In our intelligent robot 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

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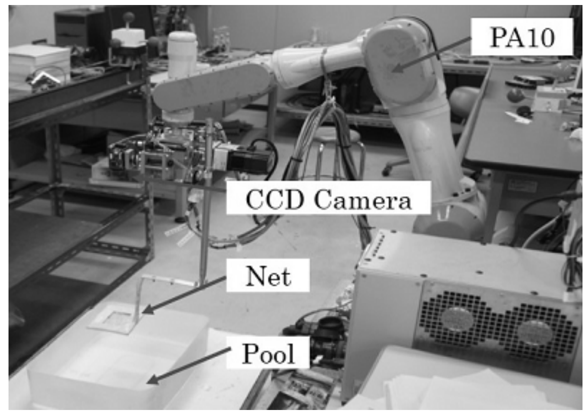


Fig. 1. Experimental system

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 under the method of Gazing GA to enhance the real-time searching ability [7].

We have learned that it is not effective for fish catching to simply pursue the escaping fish by visual servoing with velocity feedback control [8]. 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 " Learning Speed of Fish " (LSF) representing decreasing velocity of fish number caught by the net through continuous catching / releasing operation, which stand for the fish's learning speed. 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 in section 2, how to measure learning speed of fish in section 3, results of fish catching experiments in section 4 and followed by conclusion in section 5.

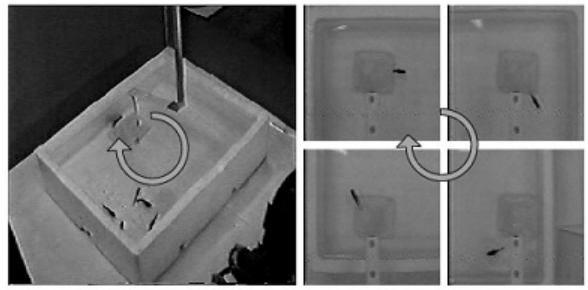


Fig. 2. Circular swimming

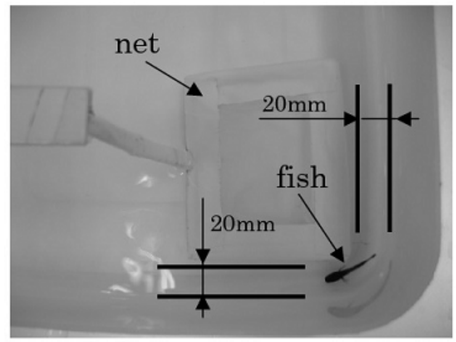


Fig. 3. Keep staying at corner

II. FISH TRACKING AND CATCHING

A. Visual servoing added chaos

The problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of $r(t) = [x(t), y(t)]^T$ in order to maximize $F(r(t))$, where $F(r(t))$ represents correlation function of a new image and matching model to a fish at time t. $F(r(t))$ is used as a fitness function of GA [7]. 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 " [7]. When the converging speed of the model to the target in the dynamic images should be faster than the swimming speed of the fish in the dynamic images, then the position indicated by the highest genes represent the fish ' s position in the successively input images in real-time. We have confirmed that the above time-variant optimization problem to solve r(t) maximizing $F(r(t))$ could be solved by " 1-Step GA " . $r(t) = [x(t), y(t)]^T$ represents the fish ' s position in Camera Frame whose center is set at the center of catching net, then $r(t)$ means position deviation from net to Fish, means $r(t) = \Delta r(t)$.

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

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

where Δr^i denotes the servoing position error detected by 1-Step GA. K P and 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 $\dot{r}_d^i$ [9]. 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,

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

Here $\Delta r^i_{fish} = \left[\ \Delta x^i_{fish}, \quad \Delta y^i_{fish} \ \right]$ is the tracking error of fish from the center of camera frame, and $\Delta r^i_{chaos} = \left[\ \Delta x^i_{chaos}, \quad \Delta y^i_{chaos} \ \right]$ 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) [10]. 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

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

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.

B. Visual servoing added randomness

The deformed random trajectories $x(t), y(t)$ are used to define Δr^i_{random} as $\Delta r^i_{random} = \left[\ x(t), y(t) \ \right]$ and by replacing a eq.(2) as follows, randomness is used on the same conditions as the time of chaos.

$$\Delta r^i = k_1 \cdot \Delta r^i_{fish} + k_2 \cdot \Delta r^i_{random} \tag{4}$$

III. FISH CATCHING EXPERIMENTS

A. Problem of fish-catching

To compare fish's escaping intelligence and robot's catching one, we kept a procedure that is catching a fish and releasing it immediately continuously for 30 minutes. 5 fish (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

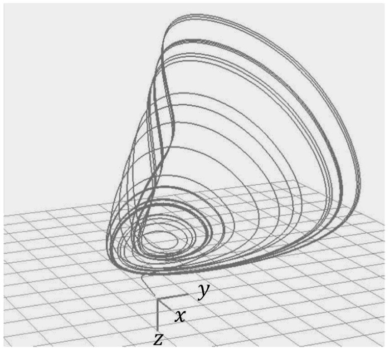


Fig. 4. Chaos trajectory

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.2 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.

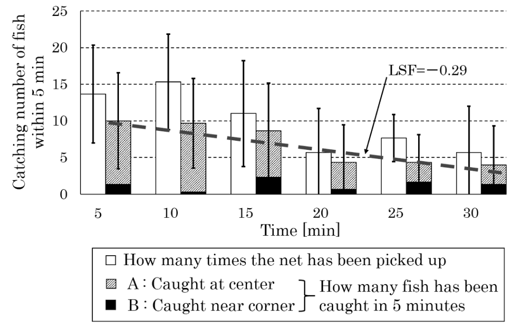
This steady state error between the net and the fish inevitably appears by fish's swimming with constant speed, since the robot's net is driver by PD controller given by (1)—control theory suggests that PD controller and ramp position input (equal to constant velocity) made steady state error. Or the fish can keep staying within the clearance between the edge of the pool and the net shown in Fig.3 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 and random 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. We generated some chaotic trajectories by nonlinear differential equations incorporated with Neural Network. One of the chaos trajectory in three-dimensional representation is shown in Fig.4. We use the chaos trajectory in this paper.

B. LEARNING SPEED OF FISH

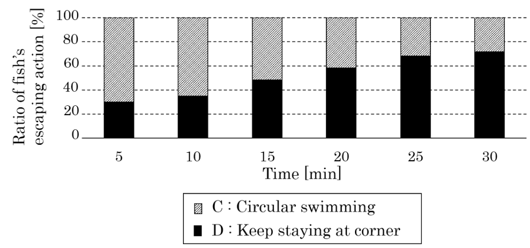
To evaluate numerically how fast the fish can learn to escape the net, we adapted Linear Least-Square approximation to the fish-catching decreasing tendency, resulting in LSF=-0.29 as shown in 5(a), which exhibit the number of fish caught by the robot in five minutes, on condition of the caught fish released into the same pool immediately. The decreasing coefficient -0.29 represents adapting or learning speed of the fish as a group when the fish's intelligence is compared with robot's catching ability. We named the coefficient as "*Learning Speed of Fish*"(LSF), since the decreasing tendency that is the value of coefficient can represent the fish's learning speed to conceive a new escaping strategies—stay at corner or swim with constant speed on a circle trajectory.

C. EXPERIMENT CONDITIONS

Experiment conditions are shown below.



(a) Catching number of fish



(b) Ratio of fish's escaping action

Fig. 5. Catching operation by using visual servoing for fish which have not been captured experience

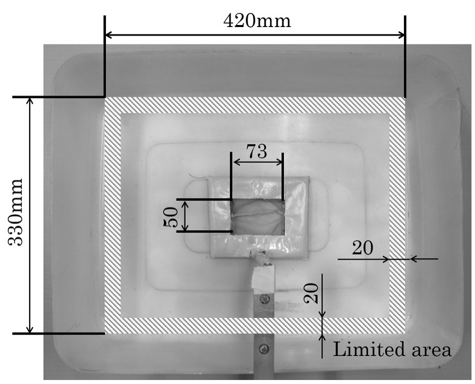


Fig. 6. Experimental pool

1. The test fish : Black Molly(length 40[mm]). We use five fish each experiment
2. The pool size : 330×420[mm] (Fig.6), and height from a bottom to the water surface : 60[mm]
3. Initial position : Net is center of the pool, and fish is randomness
4. Experiment time : 30[min]
5. Constraint condition : It is a range of 20[mm] from the side of the pool

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

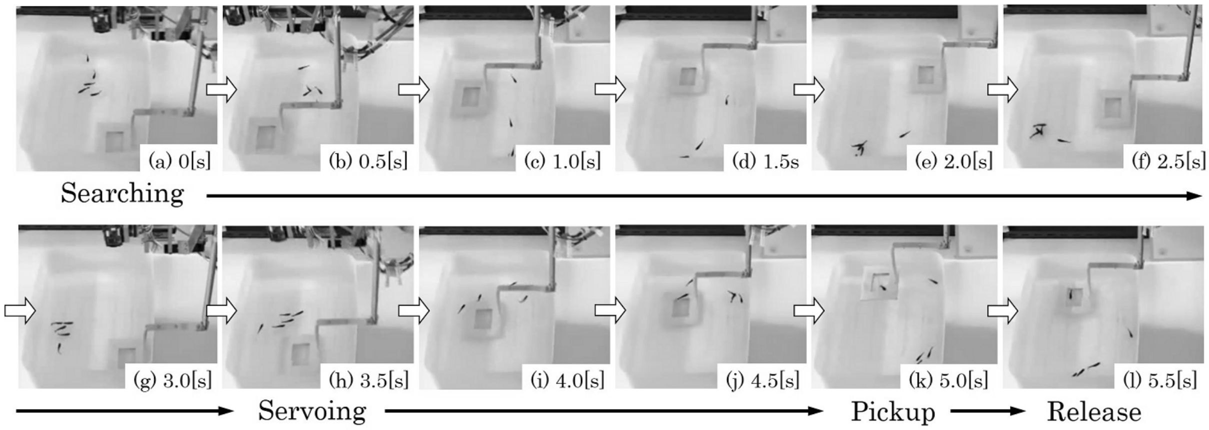


Fig. 7. Catching motion by visual servoing

as below.

(A) Caught near center
(B) Caught near corner
(C) Circular swimming (Fig.2)
(D) Keep staying at corner (Fig.3)

IV. THE RESULTS OF FISH CATCHING

A. The results against fish NOT having experienced catching operations

In this experiment, we also released 5 fish into the pool and keep tracking, catching and releasing operation continuously for 30 minutes.

1) Catching by servoing: This catching experiment is simple tracking motion by visual servoing. A state of the capturing by visual servoing in Fig.7. The result has already shown as Fig.5. As shown in Fig.5(a), 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.5(b). 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. LSF= -0.29 is the standard of the experiments that show later.

2) Catching by randomness: It is the experiment of visual servoing added random motions. A state of the capturing by random motion in Fig.8. In Fig.8(a), the robot starts recognition of the fish A. Recognition moves in A and B when the net switched the trajectory to random motion from simple visual servoing (b),(c). The fish A was captured after all.

The result is shown as Fig.9. The escaping action (D) increased gradually in Fig.9(b). In comparison with visual servoing (LSF= -0.29, Fig.5), random trajectory (LSF= -0.15, Fig.9) reduced the learning speed of fish.

3) Catching by chaos: It is the experiment of visual servoing added chaos trajectory. A state of the capturing by chaos trajectory in Fig.10.

The catching fish number kept decreasing in the former experiment shown in Fig.5. But after we embedded the

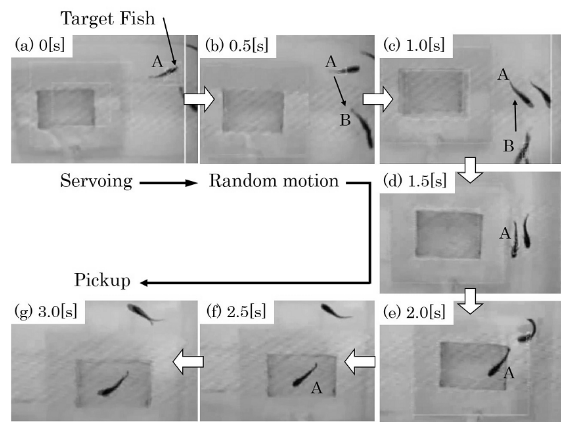


Fig. 8. Catching motion by randomness

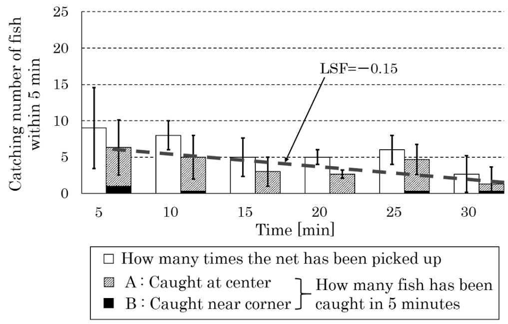
chaotic motion to net movement this time and the catching number of fish does not go down as shown in Fig.11(a). It had been thought the number would apparently decrease due to fish innate intelligence, but this experiment result is satisfying because of the chaotic motion the LSF has varied from -0.29 (Fig.5(a)) to -0.063 (Fig.11(a)). In other words, the chaotic motion have compensated the problem of fish escaping ability to escape from the catching-net.

In comparison with visual servoing (LSF= -0.29, Fig.5), chaos trajectory (LSF= -0.063, Fig.11) reduced the learning speed of fish. And the main method of the experiment latter half is capture (B).

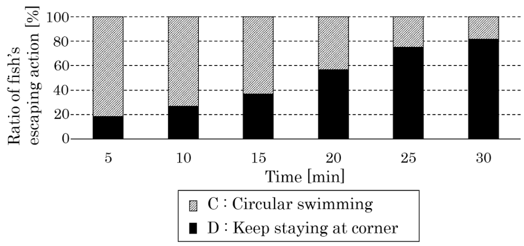
B. The results against fish having experienced catching operations

Here, we check whether chaos is effective for the fish which got an escaping action (D).

1) Catching by randomness: It is the experiment of visual servoing added random motions for fish which have been captured experience. The result is shown as Fig.12. When 15 minutes later at experiment time, the number of capture every five minutes is an average of one of them.

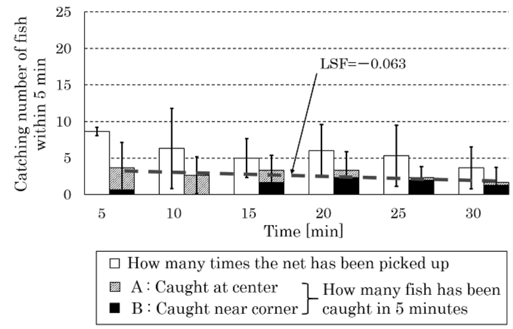


(a) Catching number of fish

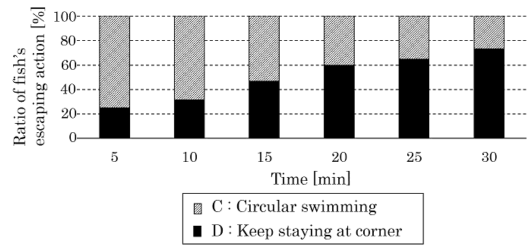


(b) Ratio of fish's escaping action

Fig. 9. Catching operation by using randomness for fish which have not been captured experience



(a) Catching number of fish



(b) Ratio of fish's escaping action

Fig. 11. Catching operation by using chaos for fish which have not been captured experience

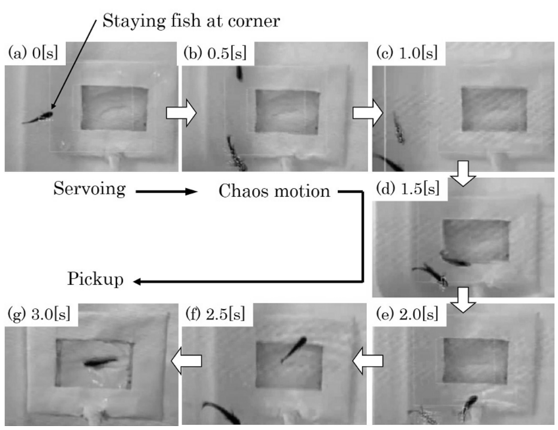


Fig. 10. Catching motion by chaos

2) Catching by chaos: It is the experiment of visual servoing added chaos trajectory for fish which have been captured experience. The result is shown as Fig.13. A constant value catching pattern (B) continues during 30 minutes. If fish escaped from the net to the pool corner, the fish come out again by chaotic motion of the net. The chaos showed a effectiveness against the fish which got an escaping action (D) staying at pool corner.

V. CONCLUSION

By this research, we measured the learning speed of fish and reduced it by chaos and random trajectories embedded into the catching-net motion in the antagonistic relationship of a robot and fish. We suggest intelligent system than the traditional one in order to exceed the intelligence of the fish and the effectively of the system is testified in real experiments. The chaos trajectory showed the effectiveness for the escaping action of fish than random motion.

The experimental results have shown that the way to capture the fish is different by using chaos motion and random motion. Furthermore, we think that this experiments succeeded in bringing about intellectual interaction between a machine and creatures. In the future, we want to consider the difference between chaos and randomness, and investigate a interaction of robot and fish in detail.

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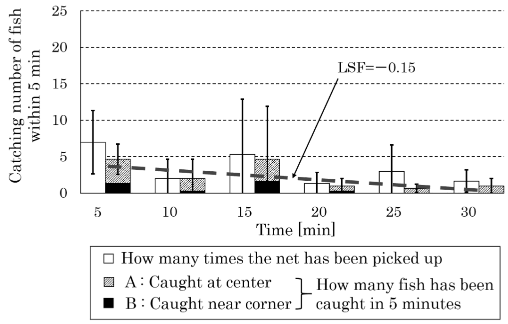
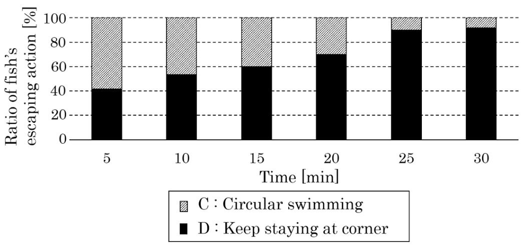


(a) Catching number of fish



(b) Ratio of fish's escaping action

Fig. 12. Catching operation by using randomness for fish which have been captured experience

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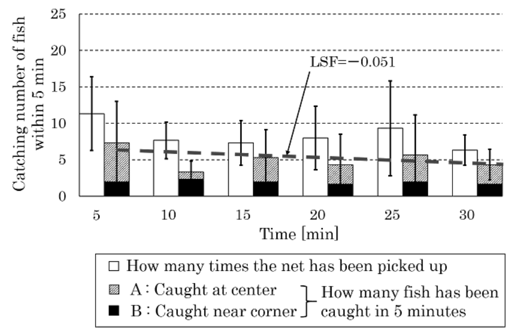
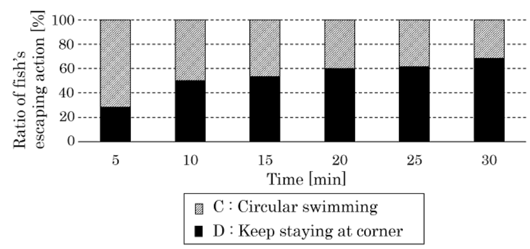


(a) Catching number of fish



(b) Ratio of fish's escaping action

Fig. 13. Catching operation by using chaos for fish which have been captured experience