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Fish Catching by Visual Servoing using Neural Network Prediction

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Abstract: This paper presents a method to predict a fish motion by Neural Network (N.N.) with on-line learning when a robot is pursuing fish-catching by a net at hand through hand-eye robot visual servoing. We assume the motion trajectory of a fish swimming in a pool be approximated by a circle with time varying radius and center position. We try to improve prediction accuracy of a fish motion by using N.N. whose inputs are radii and angular velocities in past three control-times and outputs are radius and angular velocity in the following control period. Using radius and angular velocity obtained by circular approximation, we confirmed that the proposed N.N. prediction system can maintain good prediction performances under the proposed on-line learning process.

Keywords: Neural Network, Back Propagation, Gazing-GA, Prediction.

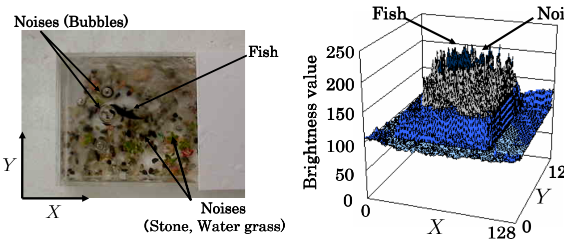
1. INTRODUCTION

Researches on catching a fish based on object feature recognition and visual servoing has been performed [1][2]. But as the catching operation by a net attached at the hand continues, the fish in the pool gradually learned the action pattern of the robot hand and began to generate intelligent avoiding behaviors against the net that keeps chasing it. We can treat this kind of fish strategy as innate intelligence to avoid its predator. As a result, the system controlled under the traditional robot system such as visual servoing based on velocity feedback failed to catch the smart fish occasionally. That is the fish has found new strategies to escape from the net pursuing it consistently. To overcome this intelligence of the fish to survive, we challenged to construct a more intelligent robot on the purpose of exceeding the fish intelligence for successful tracking and catching operation.

Under the circumstance of fishes' avoiding behaviors from the net, we consider that the robot can track the fish and catch it easier if the control system can predict its future motion. Thus, N.N. is adopted to the current robot system to learn the fish motion pattern and predict the future position[3][4]. We have tried to predict the fish position (x,y) in the future based on the position profile of the fish in the past. But it did not give us good prediction performance. In this paper, we will propose a new approach that can decrease the prediction error by introducing a circular approximation of the fish trajectory.

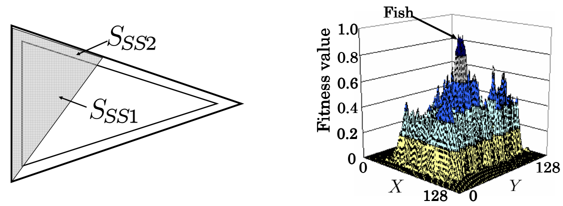
2. REAL-TIME RECOGNITION

Consider the 2-D raw-image of a target fish shown in Fig.1(a), its corresponding 3-D plot is shown in Fig.1(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.2(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



(a)2-D raw-image (b)3-D raw-image

Fig. 1 Raw-image of swimming fish



(a)Surface-strips model (b)$F_{ss}(\boldsymbol{\phi})$

Fig. 2 Surface-strips Model to search a fish

the position and orientation of surface-strips model S_{ss} is defined as $\boldsymbol{\phi}(t) = [x(t), y(t), \theta(t)]^T$, 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 $S_{ss}(\boldsymbol{\phi})$. Then the brightness distribution of raw-image corresponding to the area of the moving model is expressed as $p(\tilde{\boldsymbol{r}}_{i,j}), \tilde{\boldsymbol{r}}_{i,j} \in S_{ss}(\boldsymbol{\phi})$, then the evaluation function $F_{ss}(\boldsymbol{\phi})$ of the moving surface-strips model is given by Eq.(1).

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

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.1(a) is shown in Fig.2(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 $F_{ss}(\boldsymbol{\phi}(t))$ 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.1(a). Actually we cannot get always the highest peek in the filtered image at the position of the target object, but we can set such an environment that the highest value of $F_{ss}(\boldsymbol{\phi}(t))$ is obtained only if S_{ss1} fits to the target object being imaged.

Then the problem of recognition of a fish and detection of its position/orientation is converted to a searching problem of $\boldsymbol{\phi}(t)$ such that maximize $F_{ss}(\boldsymbol{\phi}(t))$. $F_{ss}(\boldsymbol{\phi}(t))$ 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 be applied at least only one time to one raw image input successively by video rate. We named it as "1-step GA". 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 time-variant optimization problem to solve $\boldsymbol{\phi}(t)$ maximizing $F_{ss}(\boldsymbol{\phi}(t))$ could be solved by "1-step GA".

3. GLOBAL/LOCAL GA SEARCH

3.1 Global Search

A genetic algorithm (GA) comprises search and optimization algorithms, which mimic the natural selection and evolution. A GA operates with a population of searching variables designated as individuals, considered to be the potential solutions to a given problem. The search by a GA is performed through an evolution process from generation to generation.

We employ an elitist preservation strategy of GA. The genes in GA possess the information $\boldsymbol{\phi}_i (i = 1, 2, \cdots, n)$ of the position and orientation of $i\text{-}th$ searching model. Every generational stage of simple GA's evolution, selection, crossover and mutation operators are performed to evolve the genes toward the true position and orientation $\boldsymbol{\phi}_p = [x_p, y_p, \theta_p]$ of the target fish in the raw-image. The global GA search process in the loop, always make efforts to find the highest peak indicating the fish in the whole image. When the best searching model indicated by the best gene has the highest fitness value, which means that it matches to the fish in the raw-image, the x, y, θ and x_p, y_p, θ_p get the same corresponding values.

3.2 Local Search

Like you and me, if we were to track a moving target with our eyes, at a certain degree we do not look at the surrounding and just focus our attention on the target, that is gazing it. Here, we think of how to propose a similar

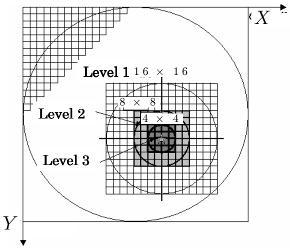


Fig. 3 Area switching

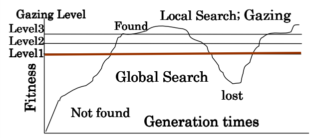


Fig. 4 Gazing switching

action as the human being to real-time visual servoing. In the reproduction of simple GA, the genes of a subsequent generation are obtained via a selection and mutation in a probability-based procedure to maintain exploration of the search domain. In our proposed local search method, the genes of the best individual is selected to be copied to all of the other individuals, thus making an intermediate population of identical individuals for possible solution of the subsequent population. Next in the reproduction process, except for that first ranking individual, in order to increase the fitness value of the others and at the same time to obtain better positional and orientational results, a mutation operation is gradually performed on the lower level bits of the genes. When the mutation is limited to four bits of the lower level, sixteen reproduction patterns can be obtained for one positional direction. When the mutation is limited to three bits, eight patterns can be obtained and when it is limited to two bits, four reproduction patterns can be obtained.

Figure 3 depicts the three level of gazing area and the level is determined by the highest fitness value, representing how much degree the possible solution matches to the position and orientation of the target fish in the raw-image. The transition of the gazing level is depending on the highest gene's fitness value as illustrated in Fig.4. As you see in the figure, we use the highest fitness value in all genes for the index of matching degree of the model and the target in the image. As it can be seen, the local search technique focuses on the highest point. Thus, when compared with the global search method of the simple GA, faster and correct detection of the target will be possible.

In practice, once the global GA has achieved the stage of the detection of a target, after reaching a certain fitness value as a threshold value, it switches to the local GA that performs the fine and fast recognition of the target, in the next generation to keep real time processing of GA. Actually, the determination of this threshold value, is environment dependent. Using the combined GA, the task executed by machine to search for a target and track the fish can be thought to be similar to the same task done by human.

4. FISH TRACKING AND CATCHING

The experimental system is explained as follows. The camera-to-fish distance is 450 [mm]. The size of the water pool is 390×460×100 (depth) [mm], and the net is

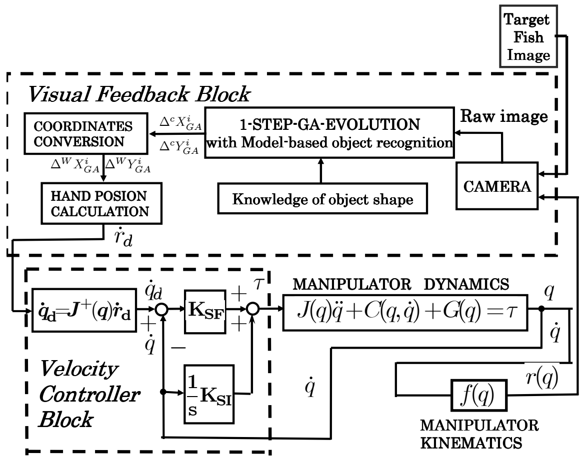


Fig. 5 Block diaguram of the controller

Table 1 Gain parameters

$\boldsymbol{K}_P$	[0.95 0.95]
$\boldsymbol{K}_V$	[0.60 0.60]
Link Number	[L1 L2 L3 L4 L5 L6 L7]
$\boldsymbol{K}_{SP}$	[3200 3200 1400 1400 1000 1000 1000]
$\boldsymbol{K}_{SI}$	[1362 1362 596 596 596 426 426]

100×125 [mm]. Catching the fish is executed by pulling up the net when the fish is within an area of 60×80 [mm] at the center of the net. In the 2-D servoing experiment, which fixes the camera-to-fish distance, the camera calibration using a parameter such as camera focal length is not performed.

The aforementioned real-time recognition system in section 2 using the shape of the fish as the knowledge base is depicted in the upper side of the block diagram in Fig.5. In the figure, $\Delta\boldsymbol{r} = [\Delta^W X^i_{GA}, ^W Y^i_{GA}]$ is the X-Y deviation from the camera center to the fish expressed in the world coordinates. The desired hand velocity at the $i\text{-}th$ control period $\dot{\boldsymbol{r}}^i_d$ is calculated as

$$\dot{\boldsymbol{r}}^i_d = \boldsymbol{K}_P \Delta\boldsymbol{r}^i + \boldsymbol{K}_V(\Delta\boldsymbol{r}^i - \Delta\boldsymbol{r}^{i-1})\ , \tag{2}$$

where $\Delta\boldsymbol{r}^i - \Delta\boldsymbol{r}^{i-1}$ is the distance change of the fish movement in a period of 1 control cycle, and $\boldsymbol{K}_P$ and $\boldsymbol{K}_V$ given in Table1 are positive definite matrix to determine PD gain. 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 $\boldsymbol{J}(\boldsymbol{q})$. 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

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

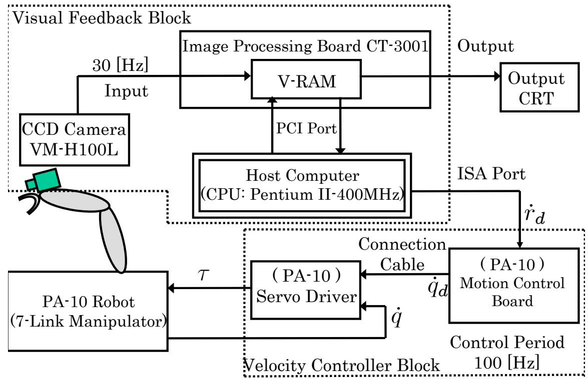


Fig. 6 Experimental set up

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 matricies to determine PI gain (Table1). The orientation of the fish is measured in real time, but in the tracking and catching experiment, the measured orientation information is not considered as shown in the above equation. The manipulator servo update rate is 100[Hz]. A diagram describing the experimental set up is shown in Fig.6.

5. CIRCULAR APPROXIMATION

Therefore, from the series of successive-three-position coordinates the resulted radius is used to serve as teacher signal for the prediction N.N.. We can say that any three coordinates can be connected by one circle. Here, $\boldsymbol{s}_{n-2} = (x_{n-2}, y_{n-2})$ and $\boldsymbol{s}_{n-1} = (x_{n-1}, y_{n-1})$ denote the fish past position coordinates, $\boldsymbol{s}_n = (x_n, y_n)$ does the current fish position coordinates, and $\hat{\boldsymbol{s}}_{n+k} = (\hat{x}_{n+k}, \hat{y}_{n+k})$ denotes the predicted fish position coordinates in the future k-control period, and $\boldsymbol{p}_n = (p_n, q_n)$ does the center coordinates of approximated circle at current time t, where n represents the fish position at the time $\Delta t \cdot n$ and $n-1$ does $\Delta t \cdot (n-1)$. From points $n-4$ to $n-2$ the center position of the trajectory is approximated as (p_{n-2}, q_{n-2}) and the radius is r_{n-2} as shown in Fig.7(a). Helping to understand how to predict with circular approximation, the circle at time $\Delta t \cdot (n-2)$ is depicted in Fig.7 (a), at $\Delta t \cdot (n-1)$ in (b), and at $\Delta t \cdot n$ in (c). The prediction $\hat{\boldsymbol{s}}_{n+k}$ at $\Delta t \cdot (n+k)$ is deduced based on the circle at $\Delta t \cdot n$ as shown in Fig.7 (d). r_n instantaneous radius of the circular trajectory of the fish is calculated in Eq.(5).

$$r_n \boldsymbol{k}_n = \boldsymbol{\rho}_n = |\boldsymbol{s}_n - \boldsymbol{p}_n| \tag{5}$$

,where $\boldsymbol{k}_n$ is a unit vector parallel to $\boldsymbol{\rho}_n$. According to the relationship at $n-2, n-1$, and n shown in Fig.8, the following equation hold:

$$|\boldsymbol{s}_n - \boldsymbol{p}_n| = |\boldsymbol{s}_{n-1} - \boldsymbol{p}_n| = |\boldsymbol{s}_{n-2} - \boldsymbol{p}_n| \tag{6}$$

The variables $\boldsymbol{p}_n = (p_n, q_n)$ can be obtained by above relations as,

$$p_n = \frac{Y_{10}}{2(X_{10})(Y_{21}) - 2(X_{21})(Y_{10})}\left\{\left(\frac{Y_{21}}{Y_{10}}\right)\right.$$

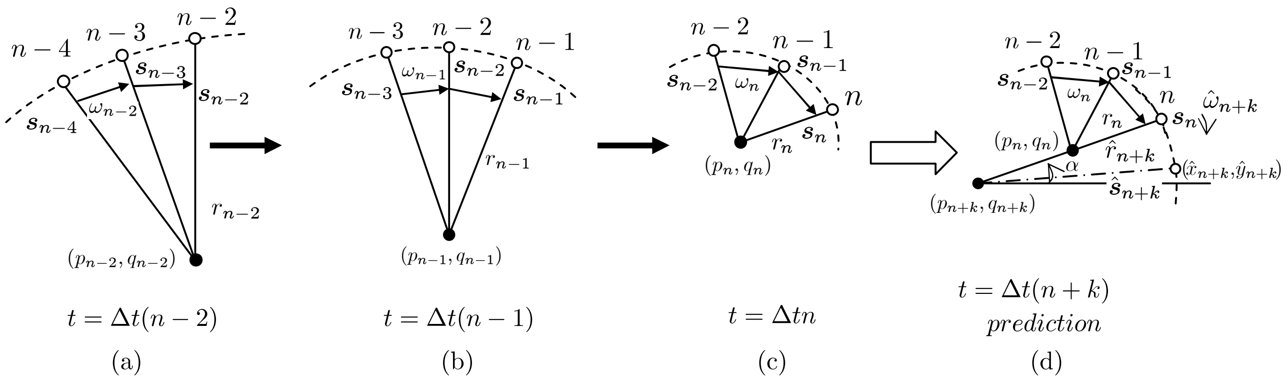


Fig. 7 Circular Approximation

$$(x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2) - (x_{n-2}^2 - x_{n-1}^2 + y_{n-2}^2 - y_{n-1}^2) \Big\}, \quad (7)$$

$$q_n = \frac{1}{2(Y_{21})}(x_{n-2}^2 - x_{n-1}^2 + y_{n-2}^2 - y_{n-1}^2 - 2(X_{21})p_n), \quad (8)$$

where

$$X_{21} = x_{n-2} - x_{n-1}, X_{10} = x_{n-1} - x_n,$$
$$Y_{21} = y_{n-2} - y_{n-1}, Y_{10} = y_{n-1} - y_n.$$

Since of the approximated circle center having been obtained based on the former calculation, the subsequent calculation procedure of radius, angular velocity can be available on the basis of calculation procedure stated before, and they are both used as teacher signal for N.N. training.

In the next step, we will concentrate on deducing the angular velocity ω_n. Here we denote $\Delta\boldsymbol{\rho}_n = \boldsymbol{\rho}_n - \boldsymbol{\rho}_{n-1}$, and consider the equation shown below:

$$\boldsymbol{t} = \boldsymbol{\rho}_n \times \Delta\boldsymbol{\rho}_n \quad (9)$$

By use of the vector $\boldsymbol{t} = [t_x, t_y, t_z]^T$, the value of angular velocity can be approximated by the covering distance by adopting radius and point $n-1$ to point n as shown in Fig.8,

$$\omega_n \fallingdotseq sign(t_z)\frac{|\boldsymbol{\rho}_n - \boldsymbol{\rho}_{n-1}|}{\Delta t \cdot r_n \boldsymbol{k}}. \quad (10)$$

We use the trigonometrical function to describe the coordinates in order to deduce the coordinate from radius and angular velocity. The current fish coordinate (x_n, y_n) is expressed by using known position (p_n, q_n), r_n and fish's heading α, which is the angle between x axis and (x_n, y_n),

$$x_n = p_n + r_n \cos\alpha \quad (11)$$
$$y_n = q_n + r_n \sin\alpha \quad (12)$$

The prediction position $(\hat{x}_{n+k}, \hat{y}_{n+k})$ after $k\Delta t[s]$ by $\hat{r}_{n+k}$ and $\hat{\omega}_{n+k}$ can be described as follow:

$$\hat{x}_{n+k} = \hat{p}_{n+k} + \hat{r}_{n+k}\cos(\alpha + k\hat{\omega}_{n+k}\Delta t) \quad (13)$$
$$\hat{y}_{n+k} = \hat{q}_{n+k} + \hat{r}_{n+k}\sin(\alpha + k\hat{\omega}_{n+k}\Delta t) \quad (14)$$

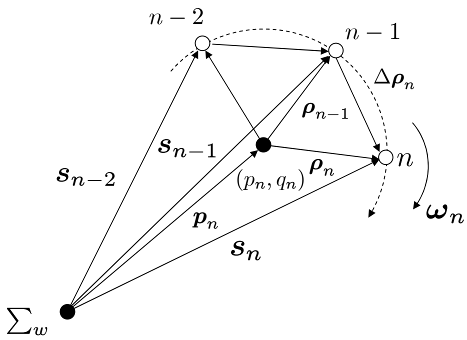


Fig. 8 Circular Approximation by using vector

6. PREDICTION

6.1 Back Propagation

In this research, the purpose is to predict and to recognize an action pattern of a fish. The movement of a fish is considered to be nonlinear, then it cannot be predicted by general methods using linear functions, which is sometimes effective in the case that linear approximation assumption is valid. Thus, we use Neural Network (N.N.) to predict the fish position in the future by adapting itself by Back Propagation (B.P.), regarded as effective learning method to approximate generally nonlinear functions. The feed forward type N.N. learns the input/output relationship by changing the value of the connection weight w_{ij} and the threshold θ_i. The output of each neuron is determined by sigmoid function $S(s_j)$ such as

$$S(s_j) = \frac{1}{1 + e^{-\alpha s_j}} \quad (15)$$

where the s_j represents the internal state of neuron, α represents gain of sigmoid function. Let the output of i-th unit in $(N-1)$-th layer be represented by u_i^{N-1}, and connecting coefficient from i-th unit in $(N-1)$-th layer to j-th unit in N-th layer be represented by w_{ij}^N, threshold value of j-th unit in N-th layer be represented by h_j^N, then the internal state of N-th neuron unit s_j^N can be expressed as,

$$s_j^N = \sum_i (w_{ij}^N \; u_i^{N-1}) - h_j^N. \quad (16)$$

By inputting s_j^N calculated by eq.(16) into eq.(15), the output value of j-th unit in N-th layer, $u_j^N = S(s_j^N)$,

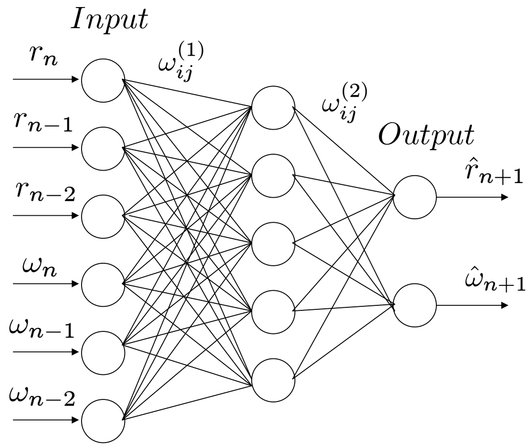


Fig. 9 Prediction by Neural Network

is obtained. In this paper, N=2,3, and the inputs to the first layer are current and past positions demoted as r_n, r_{n-1}, r_{n-2} and $\omega_n, \omega_{n-1}, \omega_{n-2}$. And the output from output layer is denoted by $\hat{r}_{n+1}$ and $\hat{\omega}_{n+1}$ as shown in Fig.9.

The renewing of the connecting coefficient value, w_{ij}, is executed by the next equation, i.e., back propagation,

$$w_{ij}(p+1) = \alpha w_{ij}(p) - \epsilon \frac{\partial Q}{\partial w_{ij}}, \quad (17)$$

where p denotes learning iteration number and Q is an evaluation function defined as squared error using the teaching signals, r_{n+1} and ω_{n+1}, which are the actual position of the fish at time t. The α and ϵ are the coefficient to determine the learning convergence speed. The connecting coefficients are changed by eq.(17) at every control period.

$$Q = (\hat{r}_{n+1} - r_{n+1})^2 + (\hat{\omega}_{n+1} - \omega_{n+1})^2 \quad (18)$$

The actual position of the fish at the time t, r_{n+1} and ω_{n+1}, is observed by real-time recognition system addressed in section 2. The above Q in eq.(18) calculates the estimation error of future fish position.

The N.N. used here, which is not recurrent type, cannot represent dynamical system, therefore it may not be thought that this N.N. can represent the dynamics of the fish driven especially by its emotion such as fear in this case. However, in this paper, the teaching signal is given as the error function based on the actual dynamical motion, and further the inputs to N.N. are results of the actual dynamics of the fish. Therefore the N.N. could be modified dynamically by using variables reflecting the real motions, as the result, the N.N. can be changed to decrease the estimation errors of this dynamical systems.

6.2 Translation of Input-output range

N.N. inputed minus value could output nearly zero value because sigmoid function outputs from 0 to 1. Therefore, we regard the range from 0 to 1 as: the first half part (0 to 0.5) is minus area, the second half part (0.5 to 1) is plus area. Range of data was W for inputed data i_{data} and after plus and minus translation of data was I_{data} as,

$$I_{data} = \frac{i_{data} + \frac{W}{2}}{W}. \quad (19)$$

Above processing makes inputed data translate 0 to 1. Neural Network outputs value 0 to 1 if that inputs value 0 to 1. We need to translate outputed data into original range:W. We use Eq.(20) for this translation.

$$i_{data} = I_{data}W - \frac{W}{2} \quad (20)$$

We use Eq.(19) and Eq.(20) for plus and minus translation of N.N..

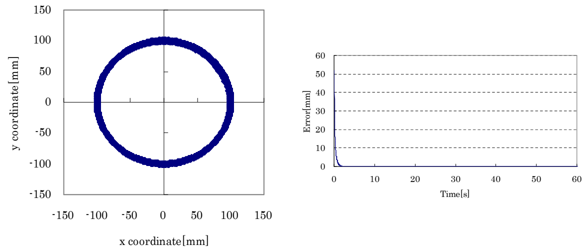
6.3 Prediction Performance

We tried test of simply trajectory used above prediction system. The experiment this time is to predict the future position in 0.48[s], with whose result shown in Fig.10, 11 and 12. Equation of Fig.10 is $x^2 + y^2 = r^2(r = 100$[mm]) and the circle is described with the addition of angle 1[deg] in every 0.016[s]. Equation of Fig.11 and 12 are $y = x$, $y = 100sin(x)$, both the line (Fig.11) and the sine graph(Fig.12) are described with the addition 1[mm] in every 0.016[s]. Both circular orbit and straight trajectory were good prediction performance. But, straight trajectory had minimum error. This error was necessary because of the using of circular approximation in prediction. Necessary error was shown in Fig.13. Therefore, we must consider a minimum error when used straight trajectory.

7. EXPERIMENT

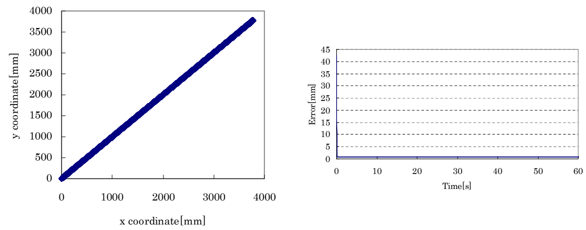
In order to make sure whether the method supposed before is effective, we perform the fish motion prediction experiment. An experiment performed catching of a fish with the system which explained with section4 for 3 minutes and examined the prediction precision. We set the number of input-layer nodes of the N.N. as 6, hidden-layer nodes as 5, output-layer nodes as 2, which is changed by Back-Propagation as shown in Fig.14. The inputs are radii of r_n, r_{n-1}, r_{n-2} and angular velocities of ω_n, ω_{n-1}, ω_{n-2} and output are predicted radius $\hat{r}_{n+1}$ and angular velocity $\hat{\omega}_{n+1}$ means the future radius at time $0.48[s]$ and angular velocity $\hat{\omega}_{n+1}$. The predicted $\hat{r}_{n+1}$ and $\hat{\omega}_{n+1}$ are used to calculate future position $(\hat{x}_{n+1}, \hat{y}_{n+1})$.

We perform the prediction used fish trajectory shown in Fig.15 and can output the prediction radius and angular velocity through back propagation method. Then, GA detects a position that fitness value is high when catching system does'nt recognize a fish, therefore a point and the straight line that broke off that there is to a graph lose sight of a fish. After time $0.48[s]$ passing, the actual values of (r_{n+1}, ω_{n+1}) can be observed by real-time recognition system and they are used for teacher signals to adjust by back propagation, then the estimation errors $\Delta r_{n+1} = \hat{r}_{n+1} - r_{n+1}$, $\Delta\omega_{n+1} = \hat{\omega}_{n+1} - \omega_{n+1}$ could be calculated as shown in the lower positioned block in



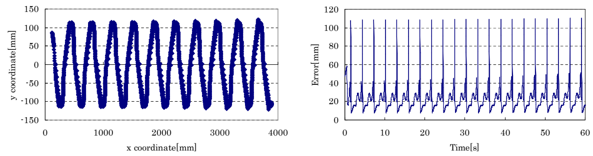
(a)Predicted circle (b)Error of position

Fig. 10 Predicted circular trajectory



(a)Predicted straight (b)Error of position

Fig. 11 Predicted straight trajectory



(a)Predicted sine (b)Error of position

Fig. 12 Predicted sine trajectory

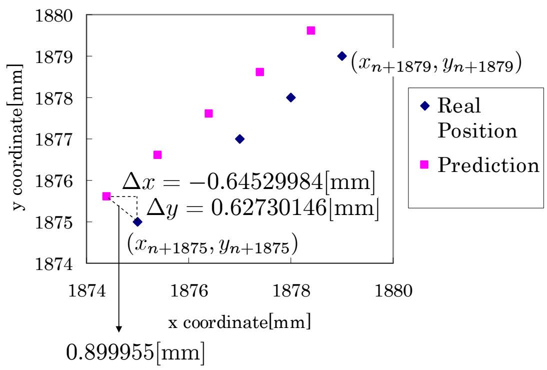


Fig. 13 Compare prediction to real position

Fig.14. Here (r_{n+1}, ω_{n+1}) can be available from Gazing-GA recognition method stated in section 3. The fish position after $0.48[s]$ compared with the former position (x_n, y_n) can be recognized by Gazing-GA directly and it is denoted by (x_{n+1}, y_{n+1}). By using Δr_{n+1} and $\Delta\omega_{n+1}$ the coefficients of the N.N. is adjusted to minimize the error at each control time in real time. Experiment result is shown in Fig.16. In this case, the average error between predicted position and real position is 269.54[mm], the manipulator which made a move based on a prediction showed unstable movement. The error over 100[mm] has arisen dozens of times by a graph of error shown in Fig.17, but was able to confirm that catching system predicted in front of the fish swam. Error over 100[mm] was considered to come out when N.N. couldn't learn at that

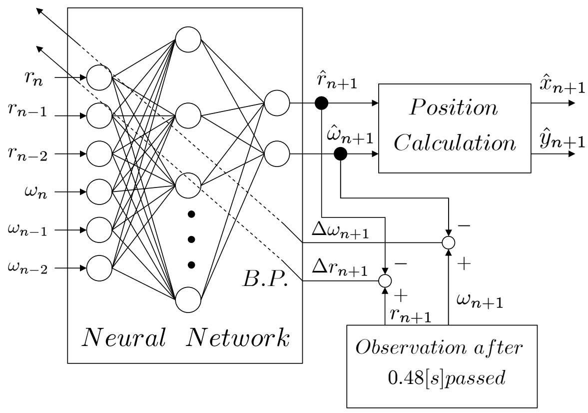


Fig. 14 Prediction Block Diagram

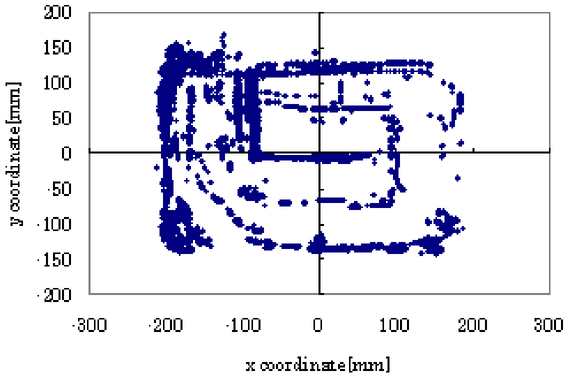


Fig. 15 Fish trajectory

time. In addition, the prediction experiment using current radius and angular velocity has also been done without the N.N.. Then observed the fish trajectory shown in Fig.18,there didn't use the N.N.. Result is shown in Fig.19. In this case, the average error between predicted position and real position is 15.61[mm], the predicted position is just in front of the fish. This average error is shown in Fig.20. Fig.17,20 have shown that high prediction precision can be obtained by using the current angular velocity. But, it is possible to predict the future position of a fish by using N.N..

8. CONCLUSION

The fish prediction can be enough and there also exists the situation that the predicted position can nearly match with the real fish position. And in this experiment, we have confirmed the effectiveness of the prediction precision. But, the distance error in experimental data is still not so perfect. Because sometimes radius and angular velocity outputed from N.N. are difference with the real value. But, if we change the N.N. coefficient properly, we can get better experiment result. Furthermore, we have comfirmed that better prediction could be obtainedby using the current radius and angular velocity than that by using the future radius and angular velocity. The reason is considered as a N.N. input problem. In future work, we willresearch under different N.N. input setting, for example, changing the prediction time. So, the problems mentioned above being settled successfully, the optimal prediction result will come out spontaneously.

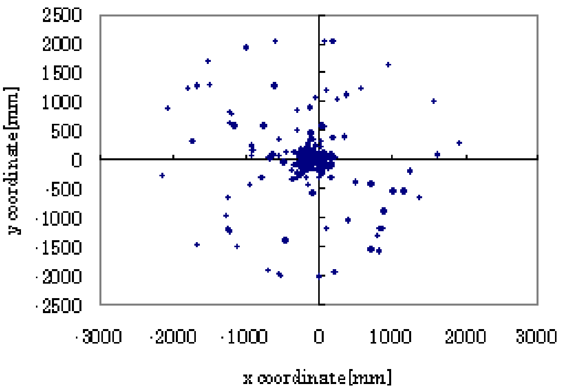


Fig. 16 Predicted fish trajectory by using N.N.

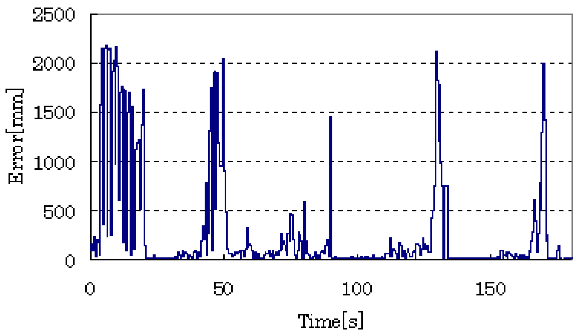


Fig. 17 Error of prediction by using N.N.

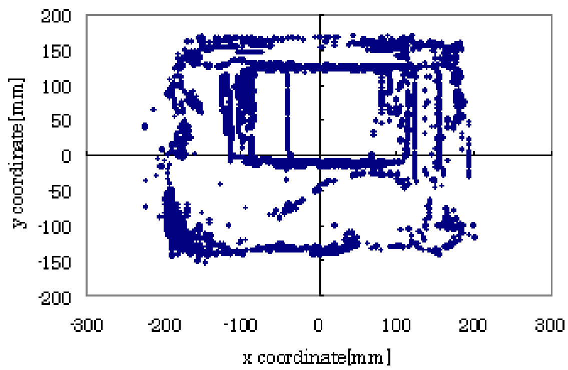


Fig. 18 Fish trajectory by using current radius and angular velocity

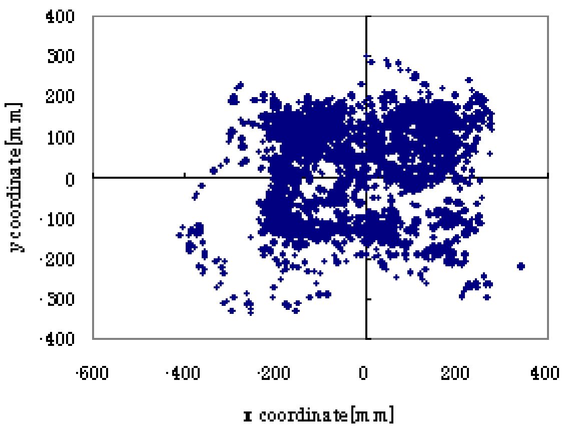


Fig. 19 Predicted fish trajectory by using current radius and angular velocity

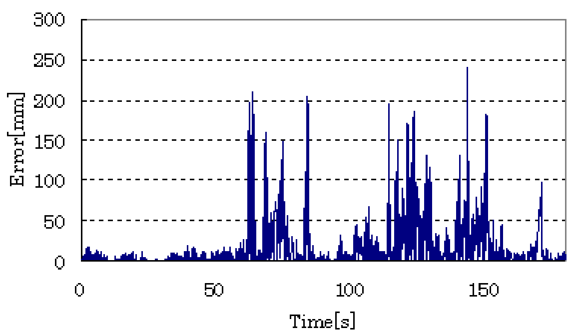


Fig. 20 Error of prediction by using current radius and angular velocity

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