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A Simulation Study on the Form of Fish Schooling for Escape from Predator

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Abstract. In this paper, on a simulation model of fish schooling considering predator's existence, we attempt an analysis of the form of school in which prey fish evades predator. We consider an evolutionary model of the fish behavior, and discuss the mechanism of schooling behavior when the school encounters with a predator. This paper then shows our computer simulation of the prey-predator system on an artificial ecology where fishes and a predator coexist, and reports well simulated prey behaviors, especially evading behaviors of the predator with advantage of schooling. On the simulation, we give an informal analysis of the transition of the form of fish school in which fishes have the evading behaviors.

1. Introduction

Most animals in groups, such as birds, fish and some colonial animals, maintain the group without a leader. They have learned to group through an evolutionary process. Grouping makes them many benefits, such as lower risk of predator, getting their food, and so on. The collective behavior without leader occurs mostly in the animals in groups whose ecological niche is low (e.g., PARTRIDGE, 1982; KREBS and DAVIES, 1993). The form of the group can change flexibly for the animals so as to perceive a risk, and then, to escape from it. In this paper, focus on the schooling behavior of fish, we propose a simulation model for studying the form of school in which prey fish evades predator.

Fish, one of the typical species which gather in aggregates, have been studied by many researchers, so as to elucidate the mechanism of the school behavior (e.g., AOKI, 1982; REYNOLDS, 1987; HUTH and WISSEL, 1994; SHIMOYAMA *et al.*, 1996; GUNJI and KUSUNOKI, 1997). Statistical approaches do not provide much elucidation for the mechanism. It is very difficult to measure and quantify the movement of fish. In this research, we consider an artificial life, model of the fish behavior, in a virtual aquarium on a computer, and then discuss the mechanism of fish school behavior by making it acquire the school behavior by evolutionary computation.

Some behavior models of fish on the basis of interaction underlying schooling are proposed from an observational standpoint (e.g., AOKI, 1982; GUNJI and KUSUNOKI, 1997).

The behavioral rules on the models are simplified to the two components of movement: speed and direction, and the components are independent or, at most, related to the location and heading of the neighbors. Schooling phenomenon is well simulated by the models. They, however, do not consider an ecology with coexistence of prey and predator. Some ecological models for coexistence of prey and predator have been reported by WARD *et al*. (2001) and NISHIMURA (2000)

In this paper, we consider an ecology of predator and prey fish, and then enhance one of the models for fish schooling with the ability to sense the predator's approach. We, after that, propose an evolutionary method for the acquisition of evading behavior against predator which is recognized as an evolved schooling behavior. This paper then shows our computer simulation of prey-predator system, and reports well simulated prey behaviors, especially evading behaviors against predator with advantage of schooling. The behaviors are comparable to real fishes in aquarium. On our simulation, we give an informal analysis of the transition of the form of fish school when it encounters with a predator.

2. Behavioral Models

In this research, we adopt a biological model concept by AOKI (1982), which is based on the observational and empirical investigation of interaction of fish behavior with its neighbors in the schooling phenomenon. Many behavioral models stand on Aoki's model (e.g., HUTH and WISSEL, 1992, 1994; INADA and KAWACHI, 1997; INADA, 2001). Aoki's model is, thus, considered to be a proper base for our research.

The concept of Aoki's model, however, does not consider the existence of a predator: i.e. no interaction between prey and predator. In this section, as the first step of this research, we enhance the model so as to examine the evading behavior of prey against predator. Our enhanced model enables us to discuss the orientational configuration for determining evading behavior. This paper, and then, provides an evolutionary approach by GA, as one solution for the discussion, in Subsec. 2.4.

2.1. The basic behavior model for fish schooling

Firstly, suppose the following *fundamental assumption* (AOKI, 1982) for all of our models:

Assumption 1

1. A 2-D world is assumed.
2. Time is quantized, and the movement of individuals determined at intervals of Δt. Decision is independent of the previous step.
3. The movement of individuals is represented by two components: speed and direction, which are stochastic variables. Speed and direction are mutually independent.
4. Interaction between individuals are restricted to the directional component. The velocity component at any time is, thus, determined independently of other individuals.

On the basic model, movement of an individual has four basic behavior patterns: *avoidance* behavior, move with a high *parallel orientation*, biosocial *attraction*, and *searching* behavior. An individual selects one from these behaviors based on the distance between the individual and its neighbors. Each of the basic behaviors has a range, and the behavior is selected by reason that the neighbor appears in the range. There are also four

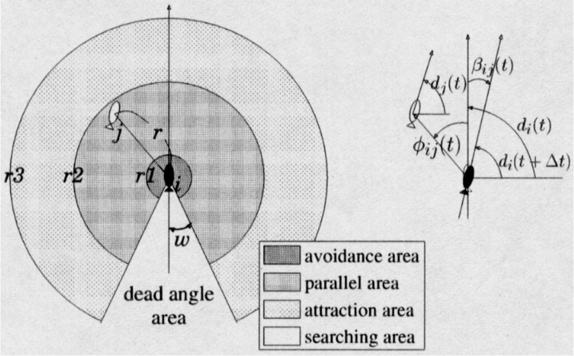

Fig. 1. Ranges of the basic behavior patterns.

ranges: *avoidance area*, *parallel area*, *attraction area*, and *searching area*. Figure 1 shows the ranges of the basic behavior patterns for a individual (black one in the figure). Let us suppose that no individual can see the outside of attraction area, that is, the *sensory field* of individual is composed of avoidance, parallel, and attraction areas. We now provide definitions for determination of behavior of individual i ($i = 1, ..., n$) in the following sections.

2.1.1 Decision of the direction of movement (normal mode)

Let i and j be individuals, and suppose that j lies in the neighborhood of i, and i reacts to j (j is called *reference individual* for i). As mentioned above, the movement of i is composed of direction and speed, and let $d_i(t)$ be the direction of i at time t. On the basic model, $d_i(t + \Delta t)$, is defined as follows:

$$d_i(t+\Delta t) = d_i(t) + \beta_{ij}(t) + \beta_0, \tag{1}$$

where $\beta_{ij}(t)$, *distinct turning angle* of i for j, is determined by any of the following equations according to which area of i j appears in (see Fig. 1):

avoidance area ($r \le r1$):

$$\beta_{ij}(t) = \min(\phi_{ij}(t) \pm 90°), \tag{2}$$

parallel area ($r1 < r \le r2$):

$$\beta_{ij}(t) = d_j(t) - d_i(t), \tag{3}$$

attraction area ($r2 < r \le r3$):

$$\beta_{ij}(t) = \phi_{ij}(t), \tag{4}$$

searching area ($r > r3$ or dead angle area):

$$\beta_{ij}(t) = \text{an angle } [-180°,+180°) \text{ chosen with uniform probability,} \tag{5}$$

where β_0 means wobble* about each decision of the direction, and it has Normal-distribution $Normal(0,\theta^2)$, and where $\min(a,b)$ returns the minimum value of a or b, by comparison between $|a|$ and $|b|$.

In *normal mode,* the direction of individual i is determined on the assumption that the determination is affected by the relation with one reference individual j. In this model, j is selected with greater probability** of nearer neighbor to i. It should be noticed that this assumption does not mean the limitation of perception; individuals leave a margin for emergencies.

2.1.2 Decision of the speed

The speed of an individual at any time is determined independently of other individuals. The speed is a stochastic variable characterized by a probability distribution. It is described by a Gamma-distribution, namely, the probability density $p(v)$ of speed v is given as follows:

$$p(v) = \frac{A^K}{\Gamma(K)} \cdot \exp(-Av) \cdot v^{K-1}, \tag{6}$$

where $\Gamma(K)$ is Gamma function***, and A and K are non-negative constant parameters. This decision method is based on Aoki's observations (AOKI, 1980).

2.2. The enhanced model considering predator's existence

In this paper, we consider an ecology where predator and prey coexist. The section describes the urgent behavior of an individual when it senses a predator approaching.

2.2.1 Decision of the direction of movement (urgent mode)

Individuals shift to *urgent mode*, when a predator appears in the sensory field of the individual. Let i be an individual, j be a reference individual for i, and e be a predator which is sensed by i. In urgent mode, the direction $d_i(t+\Delta t)$ of i at time $t+\Delta t$, is defined as follows:

$$d_i(t+\Delta t) = d_i(t) + \beta_{ije}(t) + \beta_0, \tag{7}$$

where $\beta_{ije}(t)$, *distinct turning angle* of i for j against e, is determined by the following equation whichever areas in the sensory field e and j appear in:

$$\beta_{ije}(t) = \frac{\alpha A_{ij}(t) + \beta B_{ij}(t) + \gamma C_{ie}(t) + \delta D_{ie}(t)}{\alpha + \beta + \gamma + \delta}, \tag{8}$$

where $A_{ij}(t)$, $B_{ij}(t)$, $C_{ie}(t)$, and $D_{ie}(t)$ are turning angles for *parallel with j, attracted to j, averting from e,* and *away from e,* respectively (see Fig. 2).

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*This non-deterministic factor has two effects: the naturalness in behavior and the avoidance of deadlock in rare cases.

**The probability of the selection for j is in inverse proportion to the distance between i and j.

***Note that $\Gamma(K) = (K-1)!$ if K is a non-negative integer.

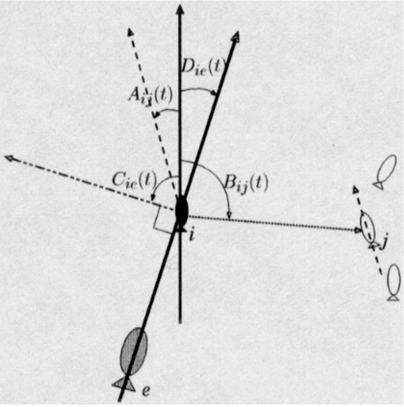

Fig. 2. Turning angles for behavior in urgent mode.

$$A_{ij}(t) = d_j(t) - d_i(t). \tag{9}$$

$$B_{ij}(t) = \phi_{ij}(t). \tag{10}$$

$$C_{ie}(t) = \min\left(\phi_{ie}(t) \pm 90°\right). \tag{11}$$

$$D_{ie}(t) = \phi_{ie}(t) - 180°. \tag{12}$$

In Eq. (8), α, β, γ, and δ are weights on the turning angles: *parallel*, *attracted*, *averting*, and *away from* respectively. These weights determine the strategy of the individual for evasion of predator.

In *urgent mode*, both reference individual j and predator e affect the direction of individual i. In this paper, we suppose that this is full perception of individual i. It should be noticed that there is no areal partition for action determination in this mode. For simplification, we also suppose that the speed component of the individual is independent of predator. The speed of an individual in urgent mode is determined by the same manner as mentioned in Subsec. 2.1.

2.3. Predator's behavior

The section gives a brief description of behavior of the predator. Behavior of the predator is characterized by two properties: specialization in chase for prey (corresponding to an individual) and a superior sensory ability and speed. Figure 3 shows the ranges of predator's behavior patterns: *prey*, *chase*, and *search*. The *sensory field* of predator is the inside of chase area.

2.3.1 Predator's movement: specialized orientation for chase

Let e be a predator and i be an individual, and suppose that i lies within the sensory field of e (we call individuals such as i *preying target* for e). The direction $d_e^p(t + \Delta t)$ of

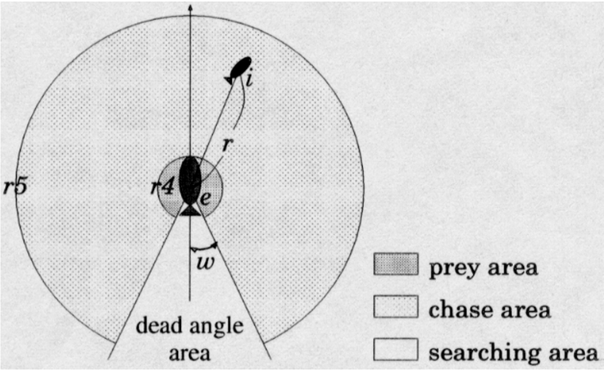

Fig. 3. Ranges of predator’s behavior.

e at time $t + \Delta t$, is defined as follows:

$$d_e^p(t+\Delta t) = d_e^p(t) + \beta_{ei}^p(t) + \beta_0, \tag{13}$$

where $\beta_{ei}^p(t)$, *distinct turning angle* of *e* for prey target *i*, is determined by any of the following equations according to which area of *e i* is caught up (see Fig. 3):

prey area ($r \le r4$):

$$\beta_{ei}^p(t) = 0, \tag{14}$$

chase area ($r4 < r \le r5$):

$$\beta_{ei}^p(t) = \phi_{ei}(t), \tag{15}$$

searching area ($r > r5$ or dead angle area):

$$\beta_{ei}^p(t) = \text{an angle } [180°, +180°) \text{ chosen with uniform probability.} \tag{16}$$

In this model, preying target *i* for *e* is selected with greater probability of nearer neighbor to *e*.

It should be noticed that the sensory field and speed of the predator are superior to the prey’s, that is, $r3 < r5$, and the speed of the predator at any time is η times faster than that determined by Gamma-distribution for individuals (see Eq. (6)).

2.4. Genetic algorithm

All of individuals have the parameters for orientational configuration for predator: α, β, γ, and δ (see Eq. (8)). Chromosomes of individuals are composed of these parameters, that is, four sections, and each of the parameters is encoded in 10 bit graycode strings (shown in Fig. 4). Each chromosome is assigned a *fitness value* that indicates the quality

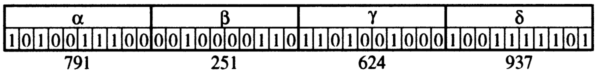

Fig. 4. An example of the chromosome structure.

of the solution derived from the chromosome. We consider, as the quality of the solution, how many time steps the individual can survive with its evading behavior based on the orientational configuration the chromosome represents.

During the execution of a GA, the population in the ecology is continually replaced by new populations. The new populations are created by applying operators (*crossover* and *mutation*) to members of the existing population. We apply one point crossover for each section of chromosome (totally four points) to two parents, and assign 5% to probability of mutation for each bit of chromosome after crossover. An individual's chance of being chosen as a parent is proportional to its fitness. If this evolution happens enough, the population should gradually improve as fitter and fitter individuals are created, please refer to MITCHELL (1996) and MICHALEWICZ (1996) for introductions to GAs.

3. Simulation

3.1. *Artificial ecology*

This section describes experiments with our artificial ecology to investigate the effects of evolution on evading behavior of its inhabitants. Evolutionary perspectives on fish schooling suggest that the environment plays a key role in its emergence. The number of factors to consider is, however, potentially infinite. In this research, we have implemented only the principle components of the ecology. We, thus, consider a 40*BL* by 40*BL* toroidal environment, where *BL* means the mean of the *body length* of individuals. For simplification, water depth, flow, and temperature and external stimuli, such as acoustic, olfactory, and photonic stimuli, are not considered in the ecology. We take N prey individuals (small fishes) and a predator (predatory fish) in the ecology. The individuals evolves their own orientational configurations for evasion of predator every discrete time steps. At each evolution, the ecology create the shortfall of individuals to the next generations, if there exists less than N individual. It should be noticed that our aim is not to perform prey-predator coexistence, but to evolve prey's evading behavior with grouping.

3.2. *Acquisition of evading behavior*

In one of the experiments, we took 100 individuals (small fish) and a predator (predatory fish) in the ecology. The behaviors of an individual and a predator comply with the behavioral models mentioned in Sec. 2. Parameters for the basic behavioral model for small fishes (see Subsec. 2.1), where $r1 = 0.5BL$, $r2 = 2.0BL$, $r3 = 5.0BL$, and $w = 30°$ for the ranges of their behavior patterns. $\theta = 15.0$ for wobble on the decision of individual's orientation, and $A = 3.3$, $K = 4.0$ for decision of individual's speed (see Eq. (6))*.

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*These parameters are given by Aoki's *standard run* (AOKI, 1982), which has a basis for schooling behavior of fish.

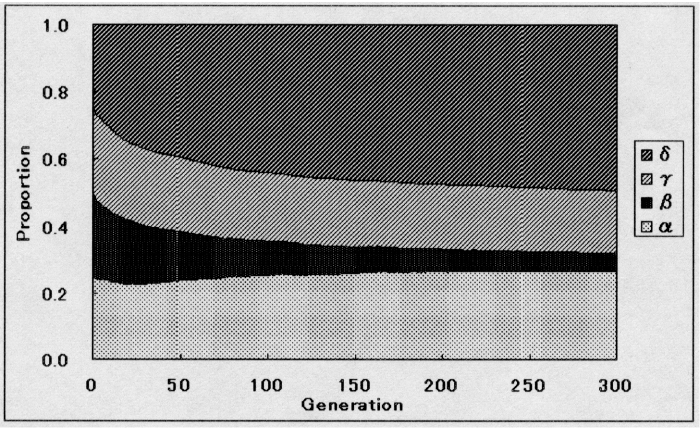

Fig. 5. Average proportions of α, β, γ, and δ in the enhanced behavioral model.

Parameters for the behavioral model for predator (see Subsec. 2.3), $BL_p = 2BL$, $r4 = 0.25BL_p$, $r5 = 5.0BL_p$, and $w = 30°$ for the ranges of its behavior patterns*, $\eta = 1.2$ for predator's dominance of speed**. On the above conditions, we have run the system for 300 generations, with 1,000 moves in each, and total of 10 runs were made.

Figure 5 shows the average proportions of parameters, α, β, γ, and δ, which determine orientation configuration of individuals for evading predators, with each generation. The result indicates that, as each generation, each of the parameters becomes more convergent; β becomes lower, δ becomes higher, and α becomes fairly higher. It is obvious that δ becomes larger so as to acquire the evading behavior. The increase in α should be noticed; this suggests that evolution takes schooling more into consideration of evading behavior.

3.3. *Observational evaluation*

We have also made an observational investigation for our model by comparing real fish behavior with the simulation. Figure 6 shows snapshots of evading behaviors by sardines and bonitos in aquarium (the right frames), and by our simulation (the left frames)***. In the simulation, we determined the setting for parameters: $\eta = 1.2$ and $\Delta t = 150$ (msec)****. This makes a situation similar to the observational result in the aquarium. The proportions of parameters α, β, γ, and δ are set at the values obtained from the above experiments (see Fig. 5). At first, a fish school and a predator face each other. Individuals

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**BLp* means the *body length* of the predator. It should be noticed that predator has the sensory field 4 times larger than that of small fishes.

**In this paper, parameters for predator have an arbitrary determination. Please refer to OBOSHI *et al.* (2002) for more experiments about different parameters.

***The movement of real fish in 3-D approximates to 2-D by the snapshots from the bottom of the aquarium.

****It should be noticed that the setting of Δt is ad hoc for our experimental environment. The suitable setting depends on the average speed of individuals and CG performance of a computer.

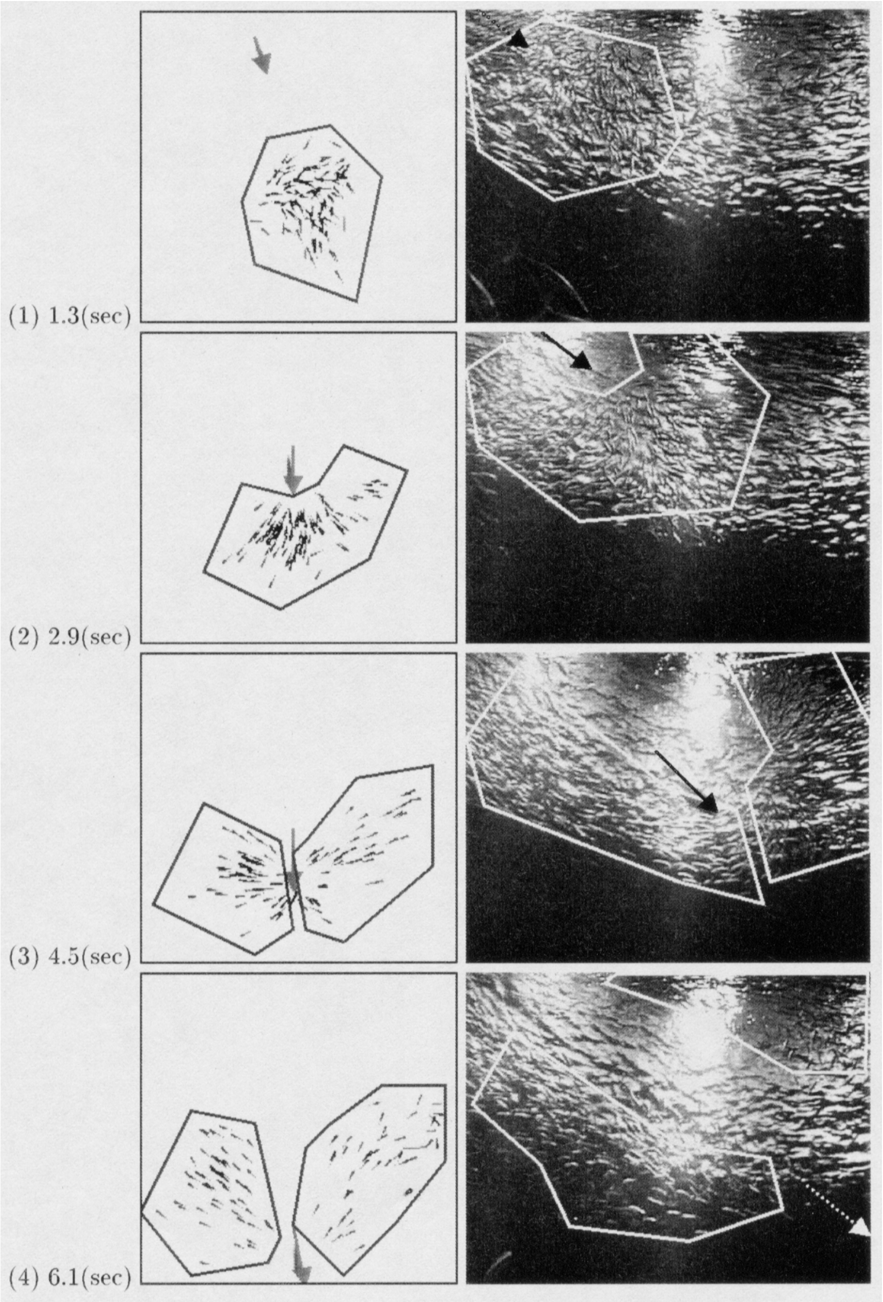

Fig. 6. A comparison of fish behaviors between the real and the simulation.

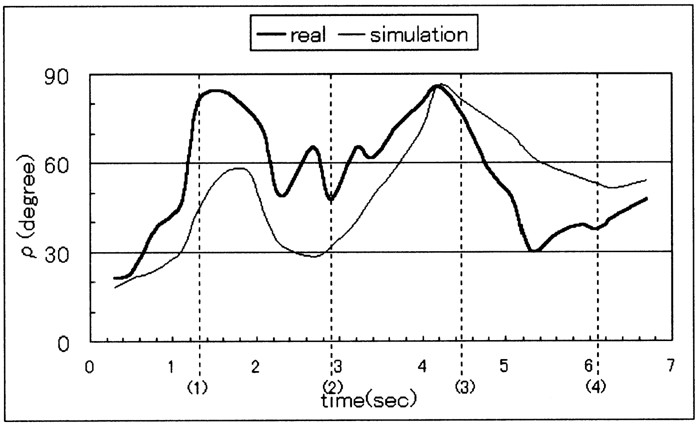

Fig. 7. Transition of polarization of fishes.

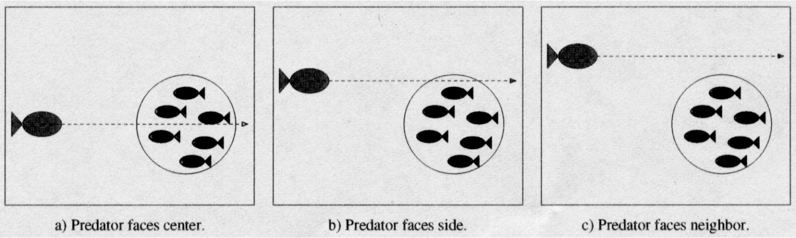

Fig. 8. Three situations of face-to-face.

in the front of school, reverse their direction in order to avert from the predator (see Fig. 6-(1)). Secondly, individuals in the rear of the school refer to the front individuals' actions, shortly after that, all individuals reverse their direction (see Fig. 6-(2)). Next time step, the predator overtakes individuals, since its speed is superior to individuals, and the prey scatter in order to evade the predator (see Fig. 6-(3)). Finally, prey which succeed in the escape from the predator make schools again (see Fig. 6-(4)).

As one of the comparisons, we have measured the polarization of the fish school. The polarization ρ characterizes the intensity of parallel orientation in the school. The polarization is defined as the average of the angle deviation of each fish to the mean swimming direction of the school. For $\rho = 0°$ the school is optimally parallel, for $\rho = 90°$ the school is maximally confused. Figure 7 shows the transition of polarization ρ of fish behaviors shown in Fig. 6. In the graph, (1), (2), (3) and (4) correspond to the labels in Fig. 6. The graph shows that two transitions have fairly similar tendency each other. The results indicate that our model and evolutionary method can evolve evading behavior of individuals adaptively to their environment, and a collective strategy for evading predator emerges by our method.

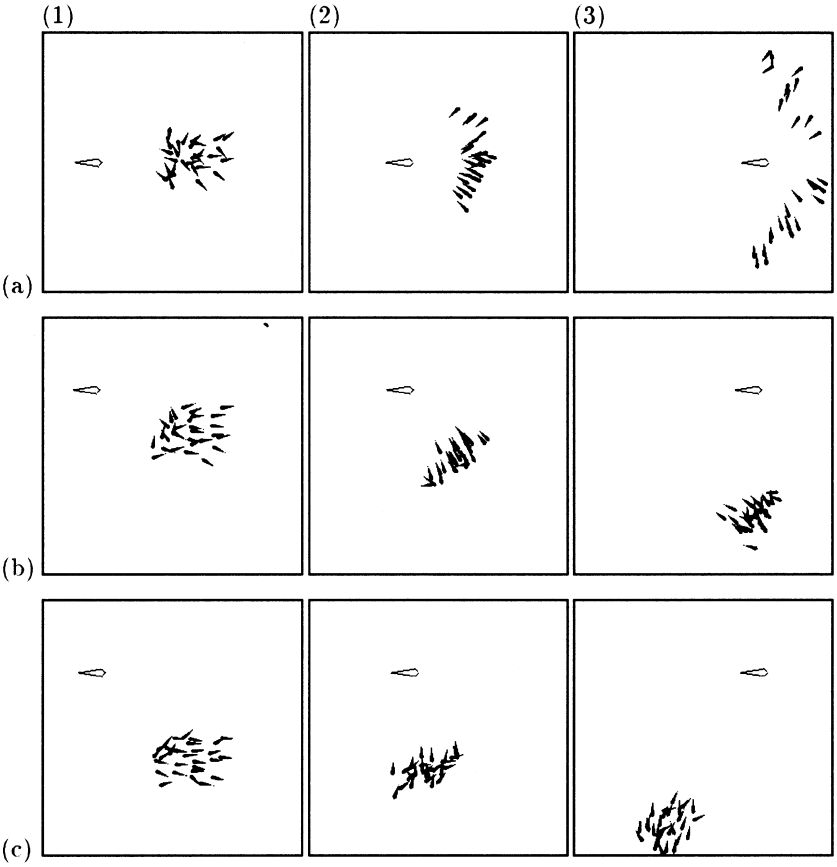

Fig. 9. Variation of the form of school.

3.4. *Transition of form of fish school in evading behavior*

This section gives a brief analysis of the form of fish school in which fishes have the evading behaviors. In this experiment, we prepared three situations in which a school and a predator are face-to-face: (a) right opposite, (b) opposite and (c) slant opposite, respectively (see Fig. 8). The size of the school were set at 30 individuals. The proportions of parameters α ,β ,γ, and δ were set at the values obtained from the above experiments (see Fig. 5). Please note that we imposed on predator's behavior for making the analysis simpler; it moves straight. Other parameters are the same with the above experiments. We firstly have observed the transition of form of school for the situations. Each situation brought the school characteristic form: (a) scattering, (b) averting and (c) collective. Figure 9 shows the snapshots of these three typical evading behaviors. In the figure, (1), (2) and (3) mean the progress of the situation: 20, 40 and 80 (step) respectively. As well as the previous section, we have measured polarization ρ of the fish school. Figure 10 shows the transition of the average polarization of school (shown in Fig. 9) with 10 trials. For

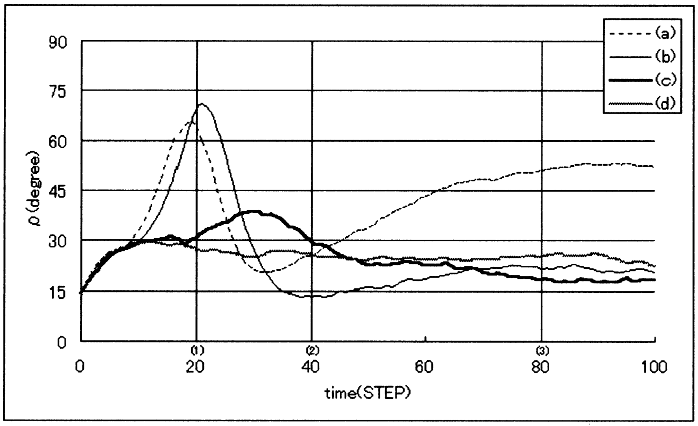

Fig. 10. Transition of polarization of school in Fig. 9.

comparison, we plotted the average polarization of the school without predator (see (d) in Fig. 10). Our behavioral model for fish schooling, as the result of this analysis, suggests a property of school in evading behavior from predator. The degree of scattering gets higher according as a school gets closer to a predator in distance and direction. After the evading behavior for a moment, the school gets polarized with caution if it succeed in the evasion, otherwise it scatters away.

4. Conclusion

In this paper, we considered an ecology where fish and a predator coexist, and then enhanced one of the models for fish schooling with an ability to sense for predator's approach. After that, we proposed an evolutionary method for the acquisition of evading behavior against predator. We also implemented simulation of a prey-predator system, and reported simulated prey behaviors, that agreed well with observations of real fish, especially evading behaviors against predator with advantage of schooling.

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