Collective or Scattering: Evolving Schooling Behaviors to Escape from Predator

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Abstract

In this paper, we consider an artificial life, model of the fish behavior, and discuss the mechanism of fish school behavior by making it acquire the school behavior by evolutionary computation. An artificial ecology where fishes and a predator coexist is considered and we enhance one of the models for fish schooling with the ability to sense a predator's approach. This paper proposes an evolutionary method for the acquisition of evading behavior against predator. This paper also shows our computer simulation of the prey-predator system, and reports well simulated prey behaviors, especially evading behaviors of the predator with advantage of schooling.

Introduction

Most animals in groups maintain the group without a supervisor leading or external stimuli. 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 (Reynolds 1987; Huth & Wissel 1994; Aoki 1982; Gunji & Kusunoki 1997, for instance).

Some behavior models of fish on the basis of interaction underlying schooling are proposed from an observational standpoint (Aoki 1982; Gunji & Kusunoki 1997, for instance). 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 the coexistence of prey and predator. An ecological model for coexistence of prey and predator has been reported by Ward (2001). The model is based on BOID by Reynolds (1987), and coevolution is well performed. The aim of this research is not to perform coevolution, but to investigate the advantages of grouping: for example, dilution, confusion and so on, with respect to protection from predator. Our model is, thus, based on a biological model concept, which is based on the observational and empirical investigation of fish behavior.

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 also shows our computer simulation of prey-predator system, and reports well simulated prey behaviors, especially evading behaviors against predator with advantage of schooling.

Behavioral Models

In this research, we adopt a biological model concept by Aoki (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 (Huth & Wissel 1992; 1994; Inada 2001, for example). 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. This paper, and then, provides an evolutionary approach by GA, as one solution for the discussion.

The basic behavior model for fish schooling

Firstly, suppose a *fundamental assumption* (Aoki 1982) for all of our models. In our models, a 2-D world is assumed. The movement of individuals is represented by two components: speed and direction, and interaction between individuals are restricted to the directional component. In addition, water depth, flow, and temperature and external stimuli are not considered.

On the basic model, movement of an individual has four basic behavior patterns: *repulsion* behavior, move with a high *parallel orientation*, biosocial *attraction*, and *searching* behavior. An individual selects one from these behaviors based on the distance between i and its neighbors. Each of the basic behaviors has a range, and the behavior is selected by reason that a neighbor appears in the range. Figure 1 shows the ranges of the basic behavior patterns for a individual (black one in the figure).

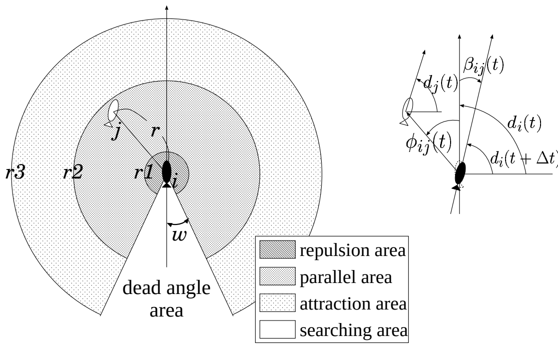

Figure 1: Ranges of the basic behavior patterns.

Let us suppose that no individual can see the outside of attraction area, that is, the *sensory field* of individual is composed of repulsion, parallel, and attraction areas.

Decision of the 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:

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

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 Figure 1):

repulsion area ($r \le r1$):

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

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

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

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

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

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

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

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 this model, reference individual j for i is selected with greater probability of nearer neighbor to i.

The velocity of an individual at any time is determined independently of other individuals. The velocity is a stochastic variable. It is described by a Gamma-distribution.

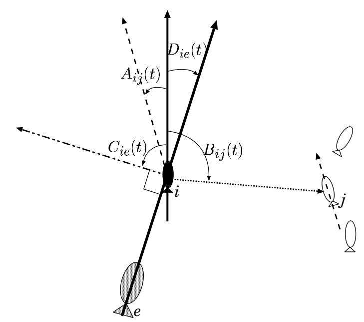

Figure 2: Turning Angles for Behavior in Urgent Mode.

The enhanced model considering predator's existence

The section describes the urgent behavior of an individual when it senses a predator approaching.

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

$$d_i^e(t+\Delta t) \quad = \quad d_i^e(t) + \beta_{ie}^e(t) + \beta_0, \qquad (6)$$

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

$$\beta_{ie}^e(t) \quad = \quad \frac{\alpha A_{ij}(t) + \beta B_{ij}(t) + \gamma C_{ie}(t) + \delta D_{ie}(t)}{\alpha + \beta + \gamma + \delta}, \qquad (7)$$

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 Figure 2). In Equation (7), 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. The velocity of an individual in urgent mode is determined by the same manner as normal mode.

Predator's behavior

The section gives a brief description of behavior of the predator. Let e be a predator and i be an individual, and suppose that i lies within the sensory field of e. In this model, preying target i for e is selected from individuals in the sensory field of e, with greater probability of nearer neighbor to e. Predator e then chases i or changes the direction randomly, if no individual is in the sensory field of e. It should be noticed that the sensory field and speed of the predator are superior than the prey's; predator's sensory field is κ times larger, and the distribution of predator's speed is η times faster than individuals. The predator e preys on i, and i disappears when e approaches i to quarter of e's length.

Ecology and Evolution

The section fixes an environment for individuals and a predator, and describes an evolutionary method for individual's orientational configuration for evasion of predator.

The artificial ecology

We consider a $40BL$ by $40BL$ toroidal environment, where BL means the mean of the *body length* of individuals. We take N prey individuals (small fishes) and a predator (predatory fish) in the ecology.At each evolution, the ecology create the shortfall of individuals to the next generations, if there exists less than N individual.

Genetic algorithm

All of individuals have the parameters for orientational configuration for predator: α, β, γ, and δ (see Equation (7)). Chromosomes of individuals are composed of these parameters, that is, four sections, and each of the parameters is encoded in 10 bit-strings. 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. 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.

Experiments

Method

In one of the experiments, we took 100 individuals (small fish) and a predator (predatory fish) in the ecology. Parameters for the basic behavioral model for small fishes, where $r1 = 0.5BL$, $r2 = 2.0BL$, $r3 = 5.0BL$, and $w = 30°$ for the ranges of their behavior patterns, and $\theta = 15.0$ for wobble on the decision of individual's orientation. Parameters for predator's superiority, where $\kappa = 4$ and $\eta = 1.2$. 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.

Results and discussion

Figure 3 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.

We have, then, investigated the influence of predator's dominance on preys' behavior. Figure 4 shows the

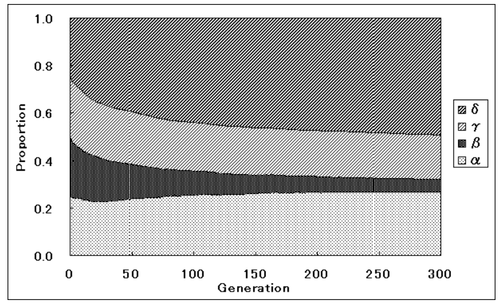

Figure 3: Average Proportions of α, β, γ, and δ in the Enhanced Behavioral Model.

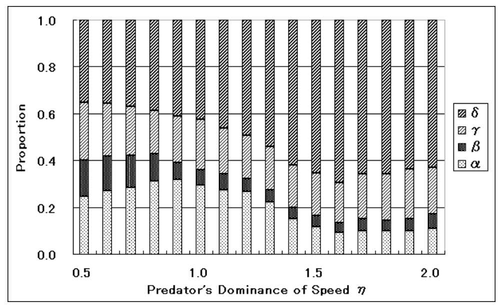

Figure 4: Average Proportions of α, β, γ, and δ Against Change η.

proportions of evolved parameter α, β, γ and δ when η, predator's dominance of speed, changes from 0.5 to 2.0 at 300-th generation. All parameters except η are the same with the above experiments. The result makes two remarks. One is that the proportion of α is moderately high, when η is lower (lower risk for prey). Another is that, as parameter η becomes higher (higher risk for prey), the proportion of δ increases; it has a maximum rate when $\eta = 1.6$, and afterwards, decreases gently. This suggests that the scattered evasion is a more effective behavior in the environment where there is higher risk of being eaten. If the predator's speed is excessively superior to individuals, individuals will be eaten no matter which evading behavior individuals have, that is, there is no strategy for evading the predator. We, thus, guess that the proportion of δ decreases if $\eta > 2.0$.

We have also made an observational investigation for our model by comparing real fish behavior with the simulation. Figure 5 shows snapshots of evading behaviors by sardines (as small fish) and bonitos (as predatory fish) in aquarium (the right frames), and by our simulation (the left frames). In the simulation, we prepared a situation similar to the observational result, with $\eta = 1.2$. The proportions of parameters α, β, γ, and δ are set by the values obtained from the above experiments (see Figure 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.

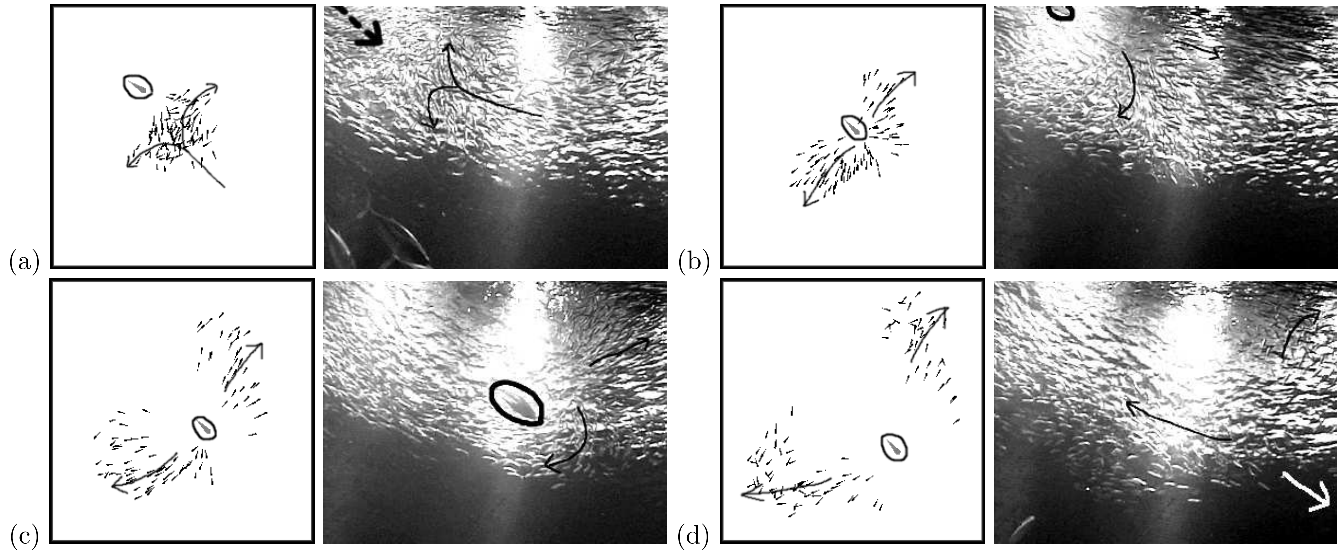

Figure 5: A Comparison of Fish Behaviors between the Real and the Simulation.

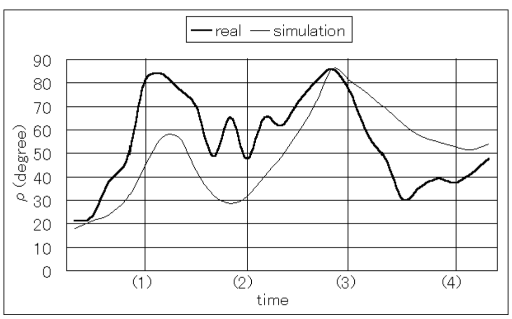

Figure 6: Transition for Polarization of Fishes.

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 6 shows that transition of polarization ρ of fish behaviors shown in Figure 5. In the graph, (a),(b),(c) and (d) correspond to the labels in Figure 5. 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.

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.

Acknowledgment

We are grateful to Mr. Watanabe and the Port of Nagoya Public Aquarium for observational support, advice and discussions. This work was supported in part by Ministry of Education, Science, Sports and Culture, Grant–in–Aid for Scientific Research under grant #11680387 and #14780307.

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