Virtual Fluid Environment on Behavior Ability for Artificial Creature

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Abstract

An environment plays an important role in behaviors acquisition for artificial creatures. Thus, the environment must obey the physical laws. In this paper, it is examined how the behavior differences appear when the artificial creature autonomously behaves in some fluid environments. We construct the approximate virtual fluid environment with low computing costs to simulate the behavior acquisition for artificial creatures. Also we propose a simulation method for artificial creatures in consideration of effects from the virtual fluid environment based on physics modeling. As a result of simulation, we verify that it is possible for the creature to acquire adaptive behaviors in different environments. After evolution, the creature behaves autonomously by leveraging effectively fluid forces in each virtual environment.

Introduction

Many computer simulations have been performed for studying acquiring behaviors, evolution, and learning methodologies on virtual artificial life creatures in the field of Artificial Life (ALife) and evolving robotics. Artificial fish swims automatically by learning its behavior controller (Tu and Terzopoulos, 1994). This study makes it easy to create fish animation. A flock simulation approach is developed based on a distributed behavioral model without setting the orbit of each bird (Reynolds, 1987). This approach makes it easy to create flock animation. The virtual creature is able to acquire its morphology and behavior by an evolutionary methodology based on the creature's competition (Sims, 1994a)(Sims, 1994b). Many studies for behavior acquisition are based on Sims' studies. Sims' model is applied to the virtual catapult creatures to evolute (Chaumont et al., 2007). This creature could throw its parts of body as far as possible. The relation for co-evolution of virtual creatures is observed by fighting each other in Sims' virtual environment (Miconi, 2008). In these days, there are many simulations for artificial creature using the physical calculating engine. It enables these creatures to obey physics law easily. "Snake-Like Robot" acquires adaptive locomotion on the ground using it (Tanev et al., 2005). This model is robust for obstacles. In these studies, the experimental environment is set as an ideal environment in a computer simulation space because they considered that the methodology of evolving and learning behavior in an ideal environment is more important than acquisition of the similar behavior in realistic environment. Therefore, the influenced force from the fluid environments to the artificial creature is not precisely analyzed. Instead, the implemented force adopts the simple calculation methods for reducing the computing time. On the other hand, in a field of numerical fluid dynamics, many fluid simulations are based on a finite element method and a particle method. The moving particle semi-implicit method makes it easy to create animation on the water surface (Koshizuka et al., 1998). A virtual anomalocaris model swims in the virtual two-dimensional water environment using the particle method (Usami, 2007). And an artificial creature behaves based on a rule method considering the fluid effect (Lentine et al., 2010). The finite element method and the particle method give accurate results. However, they consume much computational time. Therefore, it is unsuitable for a real-time simulation to acquire appropriate behaviors in the virtual fluid environment. However, we consider that the virtual environment needs to acquire a more natural policy of adaptive behaviors.

In this paper, it is examined how the behavior differences appear when the artificial creature autonomously behaves in the different fluid environments. At first, we construct an approximate virtual fluid environment which enable us to do the behavior acquisition simulation with low computing costs. This environment is constructed by setting physics parameters such as the fluid density and drag coefficients. And we propose a simulation method for the artificial creature in consideration of the fluid environment. The artificial creature imitating a flat fish is modeled by connecting rigid bodies. This creature can behave by moving its bodies. In order to control bodies and learn the behaviors, an artificial neural network (ANN) is implemented with the creature. Genetic algorithm (GA) is applied to the ANN by its evolution. We experiment to examine how the artificial creature can acquire adaptive behaviors in some fluid environments. As a result of simulation, we verify that it is possible to ac-

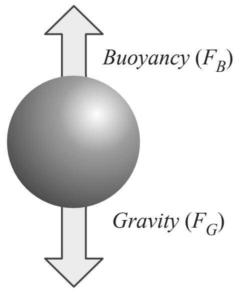


Figure 1: Modeling buoyancy

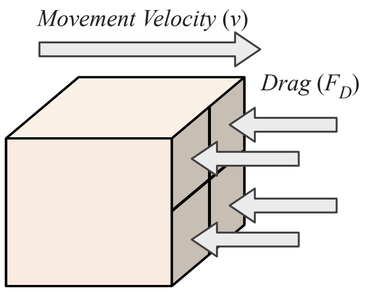


Figure 2: Modeling drag

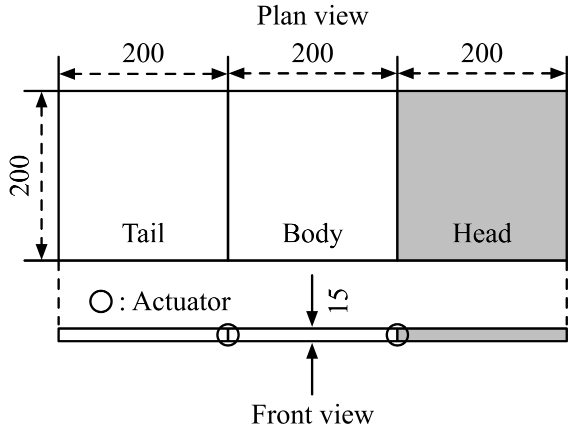


Figure 3: Artificial flat fish model

quire an adaptive behavior for the artificial creature in virtual fluid environments. And we analyze the acquired behaviors by examining a relation between fluid environments and acquired behaviors.

Construction of the Virtual Fluid Environment

We assume that the buoyancy and drag act as the forces that virtual rigid objects (sphere, rectangular parallelepipeds) receive from the fluid effect. We construct a virtual fluid environment by modeling two forces acting on the object in the fluid environment. These two forces compare to the buoyancy and drag respectively. The simulation is performed by calculating objects' movement, which obeys a physics law, resulting in an animation. We employ "PhysX (offered by the NVIDIA Corporation)" as a physical calculating engine. PhysX is applied to calculate a basic physical operation, for example, a gravity, a friction force, and collisions among virtual objects. In the virtual fluid environment the acceleration of the gravity g is 9.807[$\mathrm{m/s^2}$] We construct the fluid environments by changing the parameter of fluid density ρ.

Modeling Buoyancy

Based on Archimedes' principle, we model the buoyancy as a force whose strength F_B equals to the weight of the fluid volume which an object occupied in the fluid. This force acts on the center of the mass in the opposite direction of gravity (Fig.1). The strength of the buoyancy in the fluid environment, F_B [N], is given by equation 1,

$$F_B = \rho V g \tag{1}$$

where ρ[$\mathrm{kg/m^3}$] is the density of the fluid, V[$\mathrm{m^3}$] is the volume of the object, and g[$\mathrm{m/s^2}$] is the acceleration of the gravity.

Modeling Drag

Based on fluid dynamics, we model the drag as uniformly distributed forces to the surface of the object in the opposite moving direction (Fig.2). In the field of fluid dynamics, F_D[N] is given by equation 2,

$$F_D = C_D \frac{1}{2} \rho v^2 S \tag{2}$$

by using dynamic pressure of a flow $\frac{1}{2}\rho v^2$[$\mathrm{kg/(m \cdot s^2)}$] derived analytically as the strength of the drag in the fluid, where C_D is a scalar quantity called the drag coefficient, and S[$\mathrm{m^2}$] is the reference area of the object. The drag coefficient depends on the shape of the object. In this study, the drag coefficient of a rectangular parallelepiped is 1.50. The reference area of the object is the projection area of the object to the plane which is perpendicular to the flow.

An artificial creature can generate a propulsion force by moving its bodies because the modeled drag force is added to its bodies when this creature moves its bodies.

Experiment for Acquisition Behavior in the Different Fluid Environment

We examine how the differences appear when an artificial creature autonomously behaves in some fluid environments. It is assumed that the model must move forward as efficiently as possible. Evolutionary computing is adopted to acquire the adaptive behavior.

Artificial Flat Fish Model

We model the artificial creature by connecting rigid bodies with actuators. The modeled artificial creature imitates a flat fish, which can behave by controlling its bodies. After evaluation of this model by evolutionary computing in fluid environments, this creature behaves effectively by using leverage fluid forces in each virtual environment. Figure 3 shows an artificial flat fish model. The fish model consists of three rectangular parallelepiped with same sizes. This model has two actuators with one degree of freedom (Fig.4). The density of the model is as same as that of fluid.

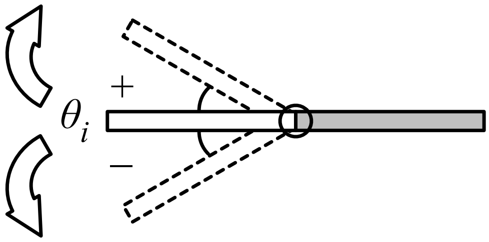


Figure 4: Model's actuator

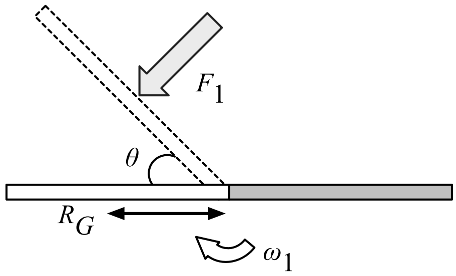


Figure 5: Modeling behavior (to bend model's body)

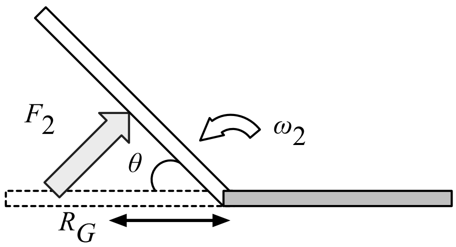


Figure 6: Modeling behavior (to unbend model's body)

Modeling Behavior for Flat Fish Model

We focus on one actuator, when the model bend upward its body, the center of gravity of its body received drag force F_1 (Fig.5). The strength of the drag force F_1 is given by 3,

$$F_1 = \frac{1}{2} C_D \rho S v_1^2 \tag{3}$$

where θ is the bend angle, r_G is the distance between the actuator and the center of gravity of its body, ω_1 is the angular velocity of the actuator and v_1^2 it the speed of the body. v_1 is given by 4,

$$v_1 = r_G \frac{d\theta}{dt} = r_G \omega_1 \tag{4}$$

Therefore, F_1 is expressed by 5

$$\begin{aligned} F_1 &= \frac{1}{2} C_D \rho S (r_G \omega_1)^2 \\ &= k\omega_1^2 (k = \frac{1}{2} C_D \rho S r_G^2) \end{aligned} \tag{5}$$

In the same way, when the model unbends its body, the center of gravity of its body receives the drag force F_2 (Fig.6), The strength of the drag force F_2 is given by 6,

$$F_2 = k\omega_1^2 \tag{6}$$

where ω_2 is the angular velocity of the actuator.

In order to move the model forward, the equation 7 is satisfied.

$$\int_\theta^0 k\omega_2^2 \sin\theta d\theta - \int_0^\theta k\omega_1^2 \sin\theta d\theta > 0 \tag{7}$$

By solving 7, the following relation

$$k(\omega_2^2 - \omega_1^2)(1 + \cos\theta) > 0 \tag{8}$$

k, $1 + \cos\theta$ are the positive value,

$$\omega_2 - \omega_1 > 0 \tag{9}$$

This equation 9 means that the model moves forward by the speed of unbending the body faster than that of bending the body. In the same reason, when the model bends its body downward, the model moves forward by the speed of unbending the body faster than that of bending the body, too.

Therefore, the model moves forward as efficiently as possible by the speed of unbending the body, which is faster than that of bending the body on each actuator.

Control Method for Flat Fish

An artificial neural network (ANN) is introduced to move flat fish model's actuators autonomously depending on information given by its sensor and actuators. Actuators are controlled by outputs of the three-layer feed-forward ANN. Table 1 shows the input and output parameters of the ANN. A transfer function for the ANN $f(x)$ is formalized by combining two sigmoid functions, given by equation 10.

$$f(x) = \frac{1}{1 + e^{(-\frac{x}{\alpha} - \beta)}} + \frac{1}{1 + e^{(-\frac{x}{\alpha} + \beta)}} - 1 \tag{10}$$

Figure 7 shows an example of the transfer function ($\alpha = 0.1$, $\beta = 5.0$). This function enables the ANN to output the zero value. The number of neurons in the hidden layer is the same as the number of neurons in the input layer. Synaptic weights of the ANN are initialized by a real random number at first. The model enables itself to behave more effectively by optimizing synaptic weights of the ANN and the gain of the transfer function.

Experimented Condition

We experiment to examine how the differences appear when the artificial creature autonomously behaves in some fluid environments. The flat fish model must move forward as efficiently as possible within a definite period of time (Fig.8).

Table 1: Setting of input and output parameters of ANN

Input	Relative angle of actuator i between rectangular parallelepiped in each time (θ_i)
	Relative angular velocity of actuator i between rectangular parallelepiped in each time (ω_i)
Output	Object angle of actuator i between rectangular parallelepiped in each time (A_i)

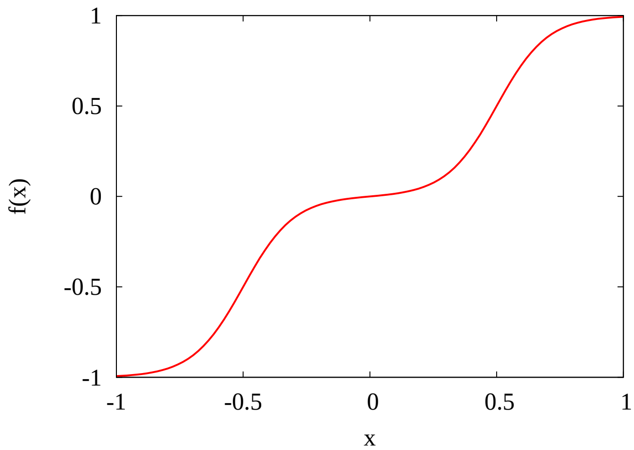


Figure 7: Transfer function for ANN ($\alpha = 0.1$, $\beta = 5.0$)

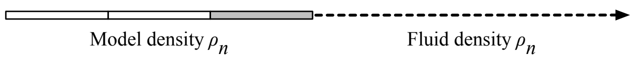


Figure 8: Initialize state of a experiment (Front view)

Table 2: Experimental condition

ANN	The number of the neuron in the input layer	5
	The number of the neuron in the hidden layer	5
	The number of the neuron in the output layer	2
	The range of an object angle	$[-30°, 30°]$
GA	Genotype	$Weight_{ij}, \alpha, \beta$
	Phenotype	F_{eval}
	Population	30
	1 Step	1/60[s]
	Simulation step	300
	Generation	250
	Crossover Probability	0.05
	Mutation Probability	0.85
	Trial times	30

Table 3: Density of each fluid environment

ρ_1	1.20$[\mathrm{kg}/\mathrm{m}^3]$ (Air environment)
ρ_2	200.0$[\mathrm{kg}/\mathrm{m}^3]$
ρ_3	400.0$[\mathrm{kg}/\mathrm{m}^3]$
ρ_4	600.0$[\mathrm{kg}/\mathrm{m}^3]$
ρ_5	800.0$[\mathrm{kg}/\mathrm{m}^3]$
ρ_6	998.20$[\mathrm{kg}/\mathrm{m}^3]$ (Water environment)

We artificially prepare six fluid environments for experiments. Table 2 shows the density ρ_n used for each fluid environment. The GA optimizes the synaptic weights of the ANN and the gain of transfer function by applying the RCGA. Table 3 shows ANN and RCGA conditions for this experiment. An evaluated value for the RCGA as a fitness function is set so that the creature moves forward as possible as it can. This evaluated value F_{eval} is given by 11.

$$F_{eval} = \sum_{t=0}^{Step} x(t) \tag{11}$$

where $Step$ is the number of step used for the simulation at each generation, $x(t)$ is a distance from a start position at each simulation step t.

Result and Discussion

We upload the movies to URL (`http://autonomous.complex.eng.hokudai.ac.jp/researches/physics-modeling/movies/nakamura`) that flat creature acquires adaptive behaviors. Figure 9 shows a diagram which draws the position of best individual at each simulation time in each environment. The angle between rigid bodies on the best individual in each environment is shown in Fig.10-15. From these results, model's bodies oscillate periodically, and the angle between its bodies propagates from the front to back in each environment. This model moves forward by oscillating its tail much more than the bodies. And the smaller the density of model is, the faster the model oscillates its bodies in the fluid environment, because the creature in the environment whose density is larger needs more energy to move its bodies than that in the environment whose density is smaller. Therefore, the smaller the density of model is, the farer the model moves forward from the start position. In addition, the speed of fish's body generates the drag forces. The speed to unbend model's body (ω_2, ω_4) is faster than that to bend its body (ω_1, ω_3) as modeling behavior for flat fish model (Fig.16). Therefore, this model can generate propulsion by applying evolutionary computations (ANN and RCGA).

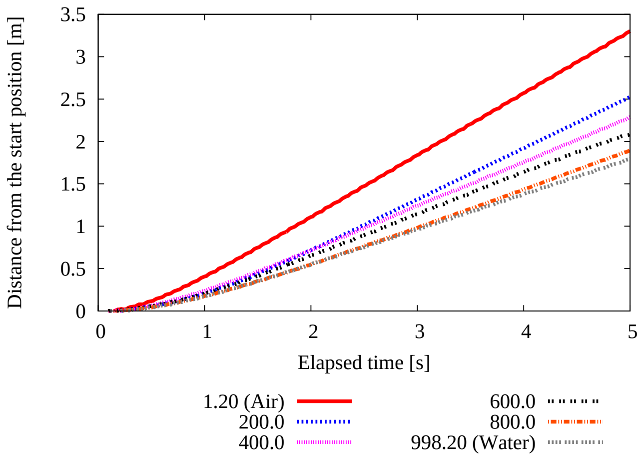
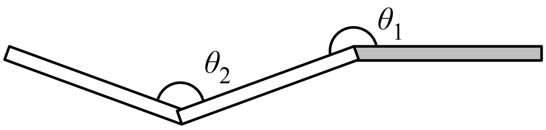


Figure 9: Relation of the fluid environment and the distance from start position



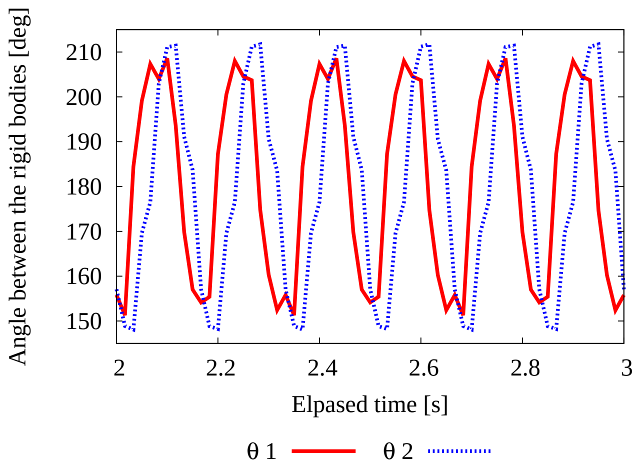


Figure 10: Angles of the rigid bodies on the best individual (Fluid density is the air)

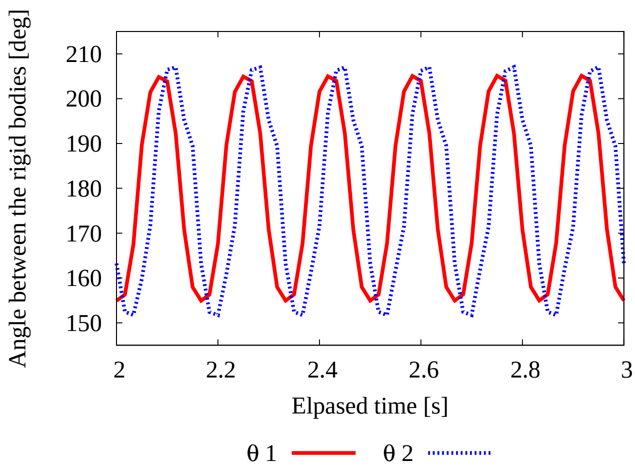


Figure 11: Angles of the rigid bodies on the best individual (Fluid density is 200.0[kg/m^3])

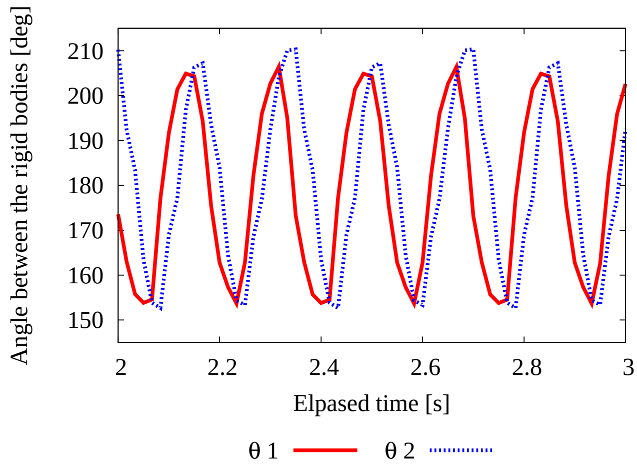


Figure 12: Angles of the rigid bodies on the best individual (Fluid density is 400.0[kg/m^3])

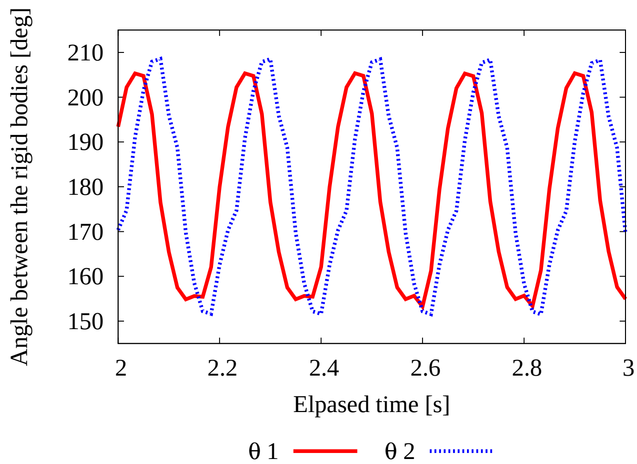


Figure 13: Angles of the rigid bodies on the best individual (Fluid density is 600.0[kg/m^3])

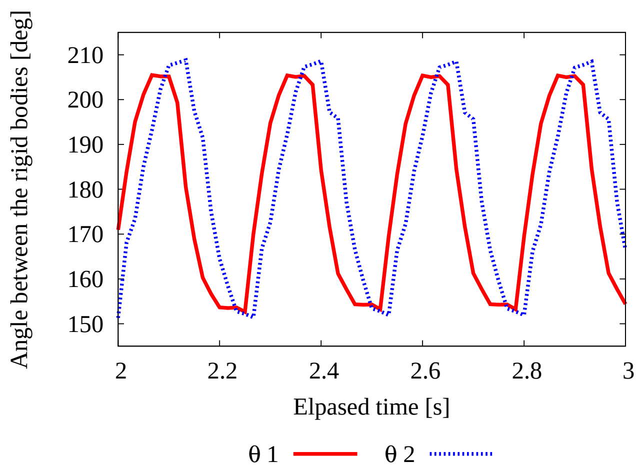


Figure 14: Angles of the rigid bodies on the best individual (Fluid density is 800.0[kg/m^3])

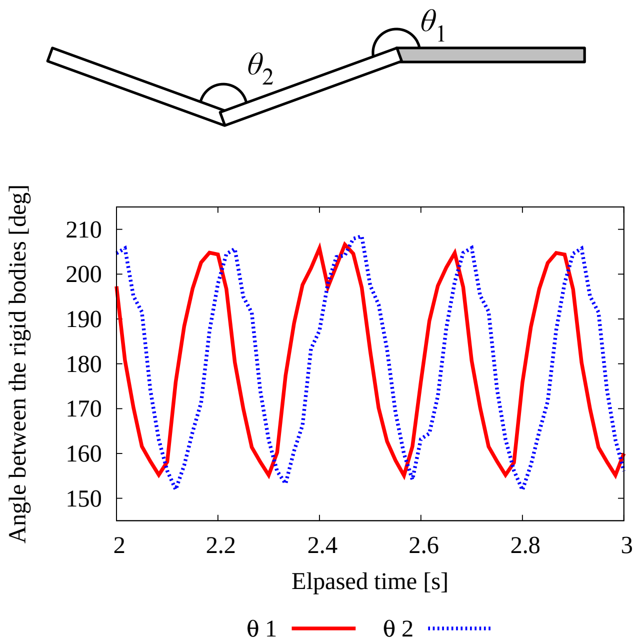


Figure 15: Angles of the rigid bodies on the best individual (Fluid density is the water)

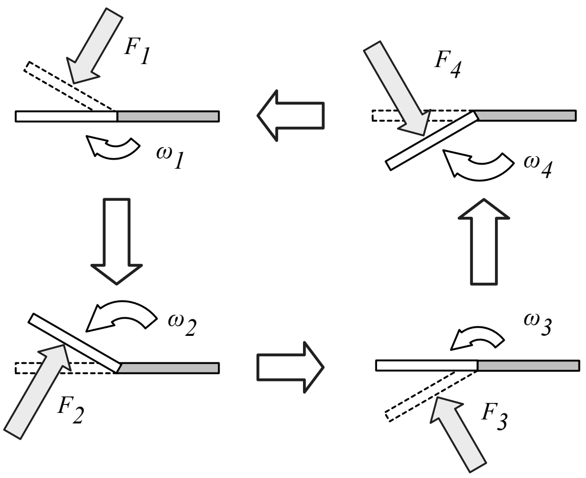


Figure 16: Mechanism generating propulsion

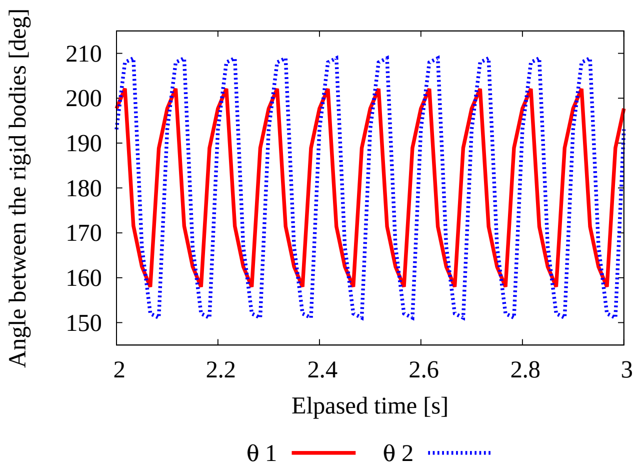


Figure 17: Angle of rigid bodies in the flat model at the 100th generation in the air environment

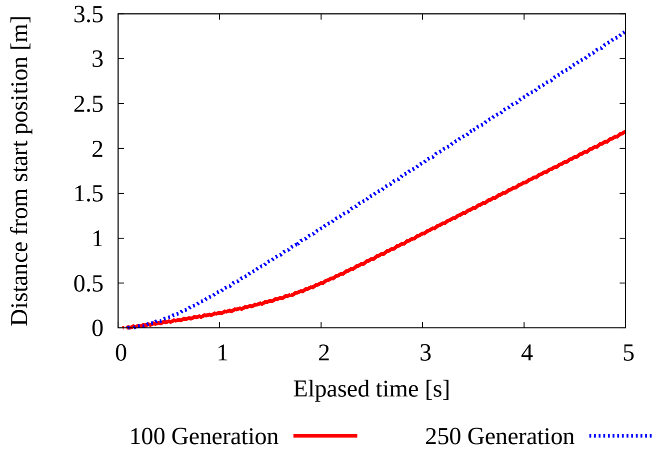


Figure 18: Relation of the generation and the distance from the start position in the air environment

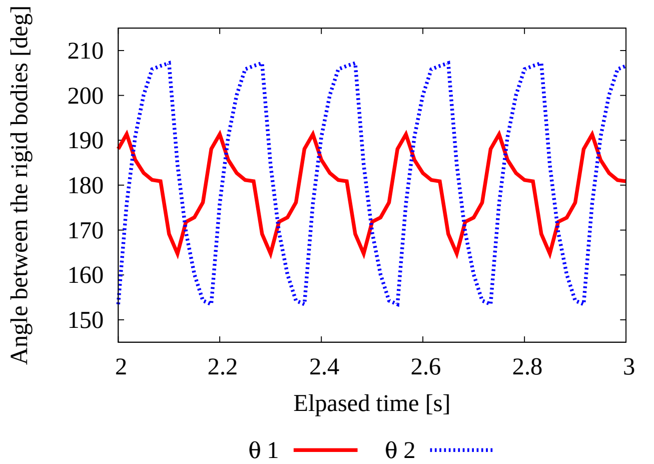


Figure 19: Angle of rigid bodies in the flat model at the 100th generation in the water environment

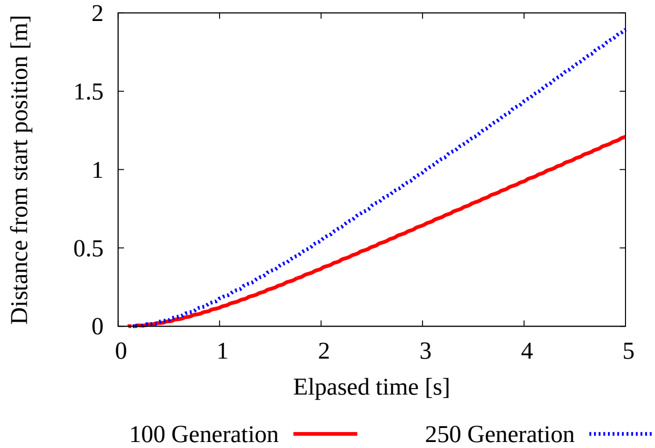


Figure 20: Relation of the generation and the distance from the start position in the water environment

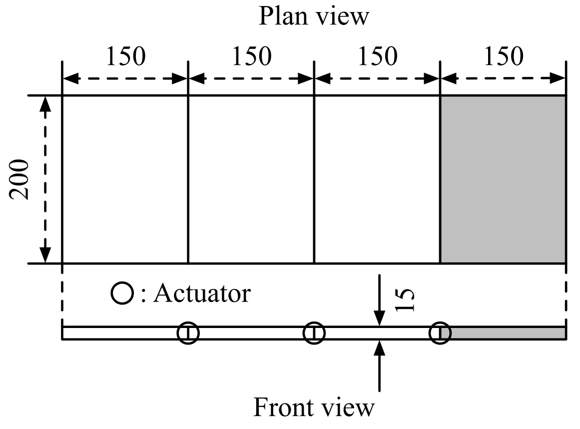


Figure 21: Three Joints Model

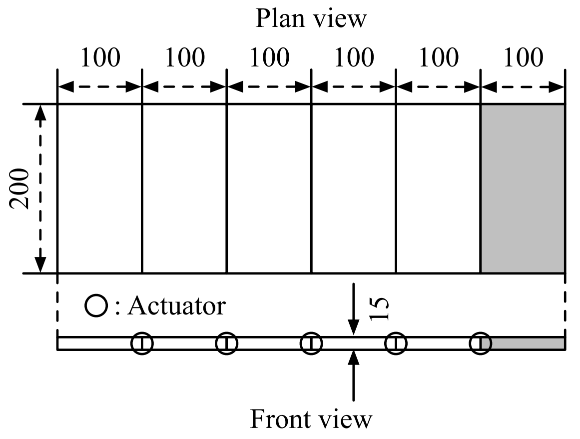


Figure 22: Five Joints Model

In the air environment, the frequency of the elite creature's body in the middle of the experiment is larger than that of creatures's body after optimizing the ANN (Fig.17). However the creature on the way of the experiment cannot move more forward well (Fig.18). Similarly, the creature on the way of the experiment cannot move more forward well in the water environment (Fig.19, 20). This creature acquires an adaptive behavior in the each environment by using evolutionary computations (ANN and RCGA), moves forward as efficiently as possible.

Additional experiment

Additionally, we examine how the topology of the artificial creature affects with the behavior ability through numerical simulation. To do so, we generate two types of the flat fish model. The modification is done by changing the number of actuators. We make a three joints flat fish model (Fig.21), and a five joints flat fish model (Fig.22). These models consist of rectangular parallelepipeds with the same size, keep-

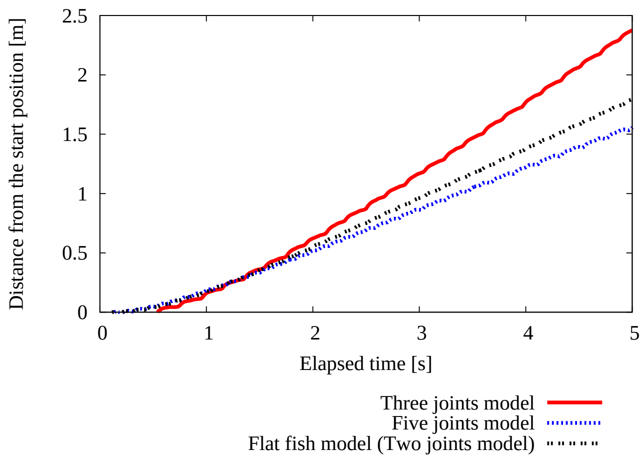


Figure 23: Relation of the number of actuators and the distance from start position

ing the total length of flat fish model (two joint model). We investigate how far two models move forward as efficiently as possible from the initial position within a definite period of time. Evolutionary computation (RCGA) is applied to all generated creatures to adapt their ANNs, which are set as controllers for the behavior. The experimental conditions for the RCGA and the ANN are shown in Table 2. The density of the fluid and model is as same as that of the water.

Figure 23 shows the position of best individual of each model at each simulation time in the water environment. Figure 24 shows the angle between rigid bodies on the best individual of the three joints model. Figure 25 shows the angle between rigid bodies on best individual of the five joints model.

From these results, three joints model move forward further than two joints model from the start position. However, five joints model do not move forward further than two joints model from the start position. Bodies of two models oscillate periodically and the angle between the creature's bodies propagates from the front to back. This creature moves forward by oscillating its tail much more than the bodies like a two joints model. And the speed to unbend each model's body (ω_2, ω_4) is faster than that to bend its body (ω_1, ω_3) as modeling behavior for flat fish model (Fig.16).

In addition, the three joints model oscillates its bodies greatly and slowly, This model generates stronger drag forces because the surface drag area is large. On the other hand, the five joints model oscillates its bodies in a small range with a fast frequency . This model generates a small drag forces because the surface drag area is small. By these experiments, it becomes clear that the flat fish model needs a proper topology of the body to move forward, that is, the topology of the flat fish model effects behaviors.

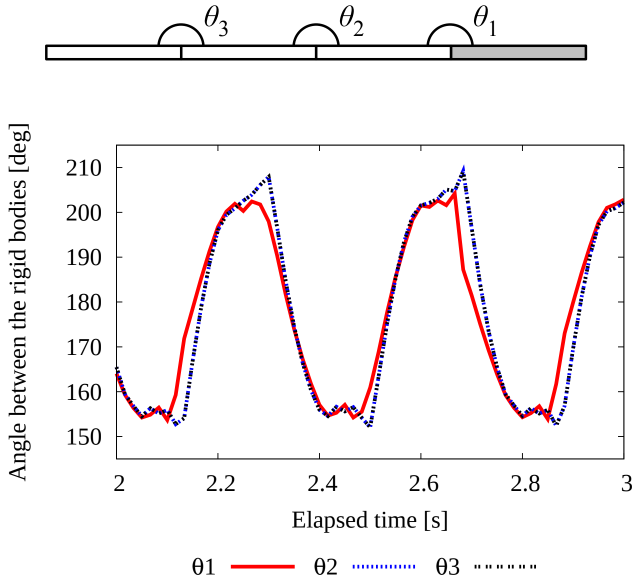


Figure 24: Angles of the rigid bodies on the best individual (three joints model)

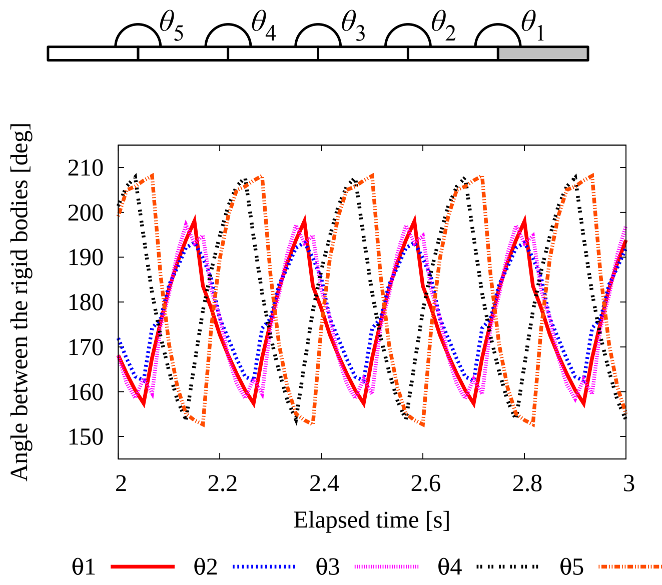


Figure 25: Angles of the rigid bodies on the best individual (five joints model)

Conclusion

In this paper, we constructed the virtual environment with low computational costs by introducing two forces comparing to the buoyancy and drag calculated by using a physical calculating engine. And we examine how the differences appear when artificial creature model autonomously behaves in some fluid environments by applying evolutionary computing (ANN and RCGA). From the result, it is possible for the model to acquire behaviors in some fluid environment. After optimizing the ANN, this model behaves effectively by leveraging fluid forces in each environment. The model's bodies oscillate periodically, and the angle between the its bodies propagates from the front to back in each environment. This model moves forward by oscillating its tail much more than the bodies. Additionally, we examine how the topology of the artificial creature affects with the behavior ability through numerical simulation. From the result, it becomes clear that the flat fish model needs a proper topology of the body to move forward.

As a future work, we would like to explore "life-as-it-could-be" by controlling the artificial creature which has many wings.

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