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Emergence of Behavior Intelligence on Artificial Creature in Different Virtual Fluid Environments

Keita Nakamura, Ikuo Suzuki, Masahito Yamamoto, and Masashi Furukawa

Graduate School of Information Science and Technology, Hokkaido University,
Kita 14, Nishi 9, Kita-ku, Sapporo, Hokkaido, 060-0814, Japan
(Tel: +81-11-706-6445)
({poco, ikuo, masahito, mack}@complex.eng.hokudai.ac.jp)

Abstract: This paper presents how the differences appear when the artificial creature, which has wings in right and left sides of the body, autonomously behaves in the air environment and in the water environment. We construct approximate fluid environments with low computing costs to simulate the behavior acquisiti on for artificial creature. Also, we propose a simulation method for the artificial creature in two environ ments. As a result of simulation, we verify that it is possible for the creature to acquire behaviors in t wo different virtual fluid environments. After evolution, the creature behaves effectively by using leverag e fluid forces in each virtual environment.

Keywords: Artificial Life, Evolutionary Computations, Control Methods

I. INTRODUCTION

Many computer simulations have been performed for studying acquiring behaviors, evolution, and learning methodologies on a virtual artificial life creature in the field of artificial life (Alife) and evolving robotics. X.Tu et al.[1] realized a behavior of an artificial fish whose controller learns swimming in the virtual water environment. C.W.Reynolds[2] proposed a flock simulation approach based on a distributed behavioral model without setting the orbit of each bird. This approach makes it easy to create flock animation. K.Sims[3][4] showed that the virtual creature can acquire its morphology and behavior by an evolutionary methodology based on the creature's competition. Many studies for behavior acquisition are based on Sims' studies. N.Chaumont et al.[5] applied Sims' model to evolution of virtual catapults. This creature could throw its parts as far as possible. There are a lot of simulations for artificial creature using physical calculating engines. They enable these creatures to obey physics law easily. I.Tanev et al.[6] simulated a side winding locomotion of a “snake-like robot”. 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 learning behavior in an ideal environment is more important than acquisition of the similar behavior in a realistic environment. Therefore, the influenced force from the fluid environments to the artificial creature is not precisely analyzed. Instead, the implemented force adopted 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 and so on. S.Koshizuka et al.[7] suggested the moving particle semi-implicit method. It makes it easy to create animation on the water surface. Y.Usami[8] did a simulation of swimming motion on Anomalocaris model in the virtual two-dimensional water environment using the particle method. The finite element method and the particle method give accurate results but consume much computational time. Therefore, it is unsuitable for a real-time simulation to acquire appropriate behaviors in virtual environment. However, we consider that the virtual environment needs to obey the physical laws for the virtual creature to acquire a more natural policy of adaptive behaviors.

In this study, we construct approximate fluid environments which enable us to do the behavior acquisition simulation with low computing costs. Also, we propose a simulation method for the artificial creature in consideration of two different environments, under-water and air. The artificial creature imitating bird is modeled by connecting rigid bodies. This artificial creature can behave by flapping their wings in two environments, which are given by changing some physics parameters such as density and drag coefficients. To control wings and learn the behaviors, an artificial neural network (ANN) is implemented with the creature.

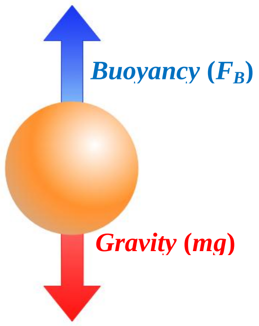


Fig.1. Buoyancy model

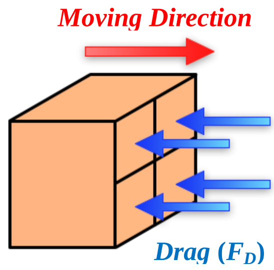


Fig.2. Drag model

Genetic algorithm (GA) is applied to ANN by its evolution. As a result of simulation, we verify that it is possible for this creature to acquire behaviors in two different virtual fluid environments. After evolution, this creature behaves effectively by using leverage fluid forces in each virtual environment. In addition, we analyze the acquired behaviors by the examining a relation between fluid environments and acquired behaviors.

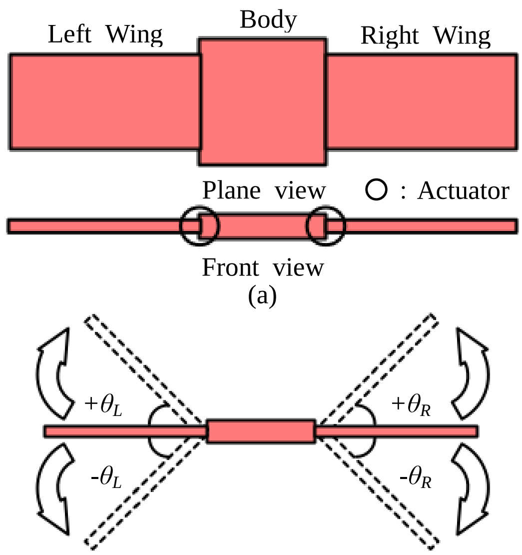
II. CONSTRUCTION OF VIRTUAL FLUID ENVIROMENTS

We assume that the buoyancy and drag act as the force that virtual objects (rectangular parallelepipeds) receive from the fluid effect. We construct a virtual fluid environment by modeling two forces acting on the object in the environment. These two forces compare to the buoyancy and drag respectively. The simulation is performed by calculating movement of the object which obeys a physics law, resulting in an animation. We use the "PhysX[11] (offered by the NVIDIA)" as a physical calculating engine. PhysX is applied to calculate a basic physical operation, for example, gravity, frictional force, collision among virtual objects, and so on. In the virtual environment, the density of the air ρ_A is 1.205[kg/m^3], the density of the water ρ_w is 998.203[kg/m^3] and acceleration of the gravity g is 9.8067[m/s^2]. We construct two fluid environments by changing the parameter of fluid density.

1. Modeling Buoyancy

Based on Archimedes' principle, we model the buoyancy as a force whose strength F_B is equal to the weight of the fluid volume which an object occupied in the fluid. This force acts on the center of 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),

$$F_B = \rho V g \qquad (1)$$



(b)

Fig.3. Artificial creature model

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

2. Modeling Drag

Based on fluid dynamics, we model the drag as uniformly distributed forces to the surface of the object in the opposite direction of moving direction (Fig.2). In the field of fluid dynamics, using the dynamic pressure of a flow $\frac{1}{2}\rho U^2$[kg/m・s^2] derived analytically as the strength of the drag in the fluid, F_D[N] is given by equation (2),

$$F_D = \frac{1}{2} C_D \rho S U^2 \qquad (2)$$

where C_D is a scalar quantity called the drag coefficient, and S[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 C_D is 1.50. The reference area of the object is the projection area of the object to the plane which is perpendicular to a flow.

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

III. EXPERIMENT FOR BEHAVIOR ACQUISITION

We examine how the differences appear when the artificial creature autonomously behaves in the air environment and in the water environment. It is assumed that the model must move upward as efficiently as possible. Evolutionary computing (EC) is adopted to obtain the adaptive behavior.

Table 1. Dimensions of each part of model

Parts	Size [m]	Density [kg/m^3]
Body	4.0×4.0×0.50	100.0 (in air) 998.2030 (in water)
Right Wing	6.0×3.0×0.250	100.0 (in air) 998.2030 (in water)
Left Wing	6.0×3.0×0.250	100.0 (in air) 998.2030 (in water)

Table 2. Input and output parameters of ANN

Input	A flapping angle of a wing for a gradient of body in each time (θ_R, θ_L)
	An angular velocity of a wing for a body in each time (ω_R, ω_L)
	An inner product of vertical upward vector and cross direction vector of its body
	An inner product of vertical upward vector and forward direction vector of its body
Output	A difference flapping angle of a wing for a gradient of body in each time (θ_R, θ_L)

1. Artificial Creature Model

We create the artificial creature by connecting rigid bodies with actuators. The modeled artificial creature imitates a bird, which can behave by controlling its wings. After evaluation of the artificial creature by EC in two environments, this creature behaves effectively by using leverage fluid forces in each virtual environment. Figure 3 (a) shows an artificial creature model. This model consists of three rectangular parallelepipeds. Table 1 shows the dimensions of each part of this model. The model has two actuators with one degree of freedom (Fig.3 (b))

2. Control Method for Artificial Creature Model

ANN is introduced to control artificial creature's actuators for flapping autonomously based on its state. ANN consists of the outputs of the three-layer feed-forward ANN. Table 2 shows the input and output parameters of the ANN. The number of the neurons in the hidden layer is same number of ones in the input layer. Synaptic weights of the ANN are initialized by a random value at first. This creature enables itself to behave by optimizing the ANN synaptic weights.

3. Experiments for Behavior Acquisition

We experiment to examine how the differences appear when the artificial creature autonomously behaves in the air environment and in the water environment. The GA optimizes the synaptic weights of an ANN. Table 3 shows experimental conditions. An evaluated value for the GA as a fitness function is set so that the creature flies as high as possible. This evaluated value F_{eval} is given by equation (3).

Table 3. Experimental condition

ANN	The number of the neuron in the input layer	6
	The number of the neuron in the hidden layer	6
	The number of the neuron in the output layer	2
	A range of an object flapping angle	[-50°, 50°]
GA	Genotype	$Weight_{ij}$
	Phenotype	F_{eval}
	Population	30
	1Step	1/120 [s]
	Simulation step	1200
	Generation number	200
	Crossover probability	0.10
	Mutation probability	0.90

$$F_{eval} = \sum_{t=0}^{Step} Height(t) \tag{3}$$

where *Step* is the number of steps used for the simulation at each generation, *Height*(t) is the height of the artificial model at step t, We use a rank selection as a reproduction operation based on the evaluated value and an elite preserving operation in the GA. We sort the individuals in ascending order of their evaluated value and preserve the best five individuals. The others are modified by crossover and mutation operations. The artificial creatures evolve, learn, and acquire the behaviors in the two fluid environments.

4. Result and Discussion

We upload the movies to URL[12] that the artificial model acquired behaviors in two fluid environment. Figure 4 shows the angle between the body and both wings in the air environment for one second after learning. Figure 5 shows the angle for one second after learning in the water environment.

From these results, in the air environment, both wings of the model oscillate periodically. The speed to swing down the wings is faster than that to swing up the wings. Therefore, the model after leaning can move upward by rather swinging down the wings than swing up the wings to generate a drag difference (Fig.6 (a)) and needs to balance itself by generating the force larger than gravity. On the other hand, in the water environment, the angle between the body and both wings propagate from the right wing to the left wing. The angle between the body and left wing is larger than that between the body and the right wing. Therefore, the

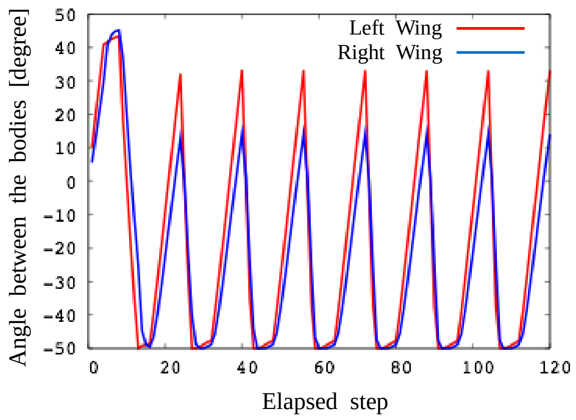


Fig.4. Angle of body and both wings in the air environment

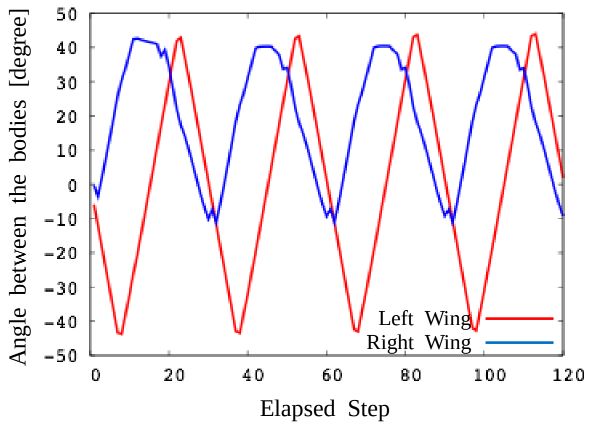
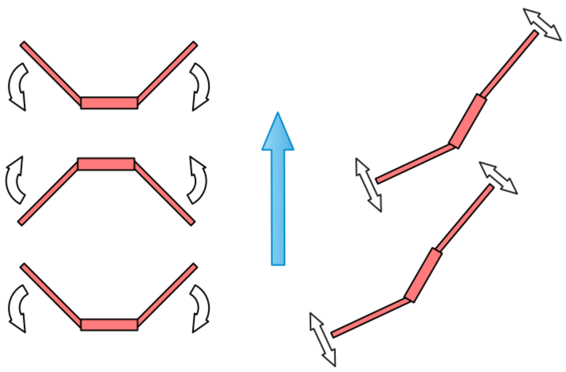


Fig.5. Angle of body and both wings in the water environment

model after leaning can move upward by oscillating periodically like a sea snake (Fig.6 (b)). The right wing plays a role of head, and the left wing plays a role of tail.

VI. CONCLUSION

In this paper, we modeled the received effect from the fluid environment by introducing two forces comparing to buoyancy and drag and constructed two fluid environments (in air environment and in water environment) by changing the parameter of fluid density. Secondly, we examine how the differences appear when the artificial creature model autonomously behaves in the air environment and in the water environment. From the result, it is possible for the model to acquire behaviors in two different virtual fluid environments by using evolutionally computations (ANN and GA). After learning, this creature behaves effectively by using leverage fluid forces in each virtual environment. In a future, we would like to experiment that the artificial creature which has wings in right and left sides of the body acquires behaviors to move freely in the air environment and in the water environment by controlling flapping angles and feathering angles. Additionally, we would like to explore "life-as-it-could-be" by controlling the artificial creature which has many wings.



(a) Air environment (b) Water environment
Fig.6. The model acquired behavior

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