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Behavior emergence of virtual creature living in complex environments

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Abstract: This study aims at establishing a new computer aided animation method using the agent-based and physics modeling based animation. The specific problem we treat in this paper is to acquire an adaptive behavior of a virtual creature placed in a complex environment and to create the animation of its behavior automatically. The virtual creature is regarded as an autonomous agent who has sensors, actuators, and controllers. For controlling the virtual creature, ANN and CPG are adopted as the controllers. Optimization algorithm is introduced for learning the controllers. Numerical experiments proved that the virtual creature acquires effective motions (walking, swimming) to pursuit the destination, and to avoid the obstacle and other creatures.

Keywords: Artificial Neural Network, Central Pattern Generator, Evolutionary Algorithm, Artificial Life

I. INTRODUCTION

Computer-aided animation using the computer graphics technology becomes more important in various fields such as physics, engineering, entertainment, and medical science. In entertainment field, physics modeling based simulation for generating the realistic object motion has attracted researchers attention, and many works have been presented in this decade[1],[2]. On the other hand, the physics modeling based animation for artificial-beings, which can autonomously behave as living organisms in the earth, is still an undergoing research matter. A motion capture method is mostly adopted to create the animation for the artificial-beings. However, this method consumes lots of time and requires an expert knowledge for creating the animation.

The agent-based approach is efficient solutions for overcoming problems that the motion capture method has. This study aims at establishing a new computer aided animation method using the agent-based and physics modeling based animation. The specific problem we treat in this paper is to acquire an adaptive behavior of a virtual creature placed in a complex environment and to create the animation of its behavior automatically. The complex environment means a dynamically changed environment caused by fluid influences, obstacles and interaction among agents.

For generating a control signal with rhythmic pattern which is observed in living organisms, we implement a controller of the virtual creature by a combination of a central pattern generator (CPG) and an artificial neural network (ANN).

Evolution of the virtual creature is realized by learning ANN and CPG. An optimization algorithm is introduced into learning for evolving the virtual creature placed in complex environments. An evaluation function to evaluate the behavior of the virtual creature for the optimization algorithm is based on radical characteristics of life such as energy conservation, target pursuit and evasion from obstacle. This evaluation function is applicable to evaluate virtual creature which has any shapes.

II. VIRTUAL ENVIRONMENT

All experiments described below are performed under virtual environment which fundamental physical law is considered. We adopt a dynamics engine for implementing the fundamental physical law with virtual environment. The adopted engine is PhysX, presented by NVIDIA[4]. PhysX allows us to simulate physical dynamics and phenomenon of a rigid object such as gravity, action-reaction, friction, restitution, and collision. Additionally, this environment is implemented influenced forces caused by fluid.

II. VIRTUAL CREATURE

1. Salamander model

A salamander is modeled as a virtual creature. The salamander can behave itself under the water and air resistances namely a complex environment. Then, we examine the salamander behavior by evolving it in the complex environment. The salamander consists of seventeen rigid objects whose geometric and physical data are shown in Table1. The salamander has two sensors and twelve actuators (see Fig.1).

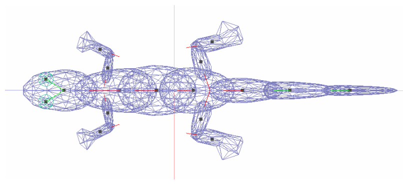


Fig.1. Salamander model

Table1. Data of components of the salamander model

Body Components	Value
Density	ρ=1000 [kg/m^3]
Restitution	0.2
Static friction	0.2
Dynamic friction	0.1
Limb Components	**Value**
Density	ρ=1000 [kg/m^3]
Restitution	0.2
Static friction	0.9
Dynamic friction	0.8

2. Sensors

Optical sensors can detect a light strength S_L from a light source placed in a virtual space. S_L is defined by (1), where θ_L is an angle between the light source and the sensor direction, and B_r is brightness of an light source. Inclination sensors detect a Inclination of sensors S_L according to (2), where θ_I is a inclined angle. Pressure sensors detect a environmental pressure S_P according to (3). These values turn into inputs of the salamander controller.

$$S_L = \begin{cases} -\pi/2 < \theta_L < \pi/2 : & B_r \cos\theta_L \\ otherwise \quad : & 0 \end{cases} \tag{1}$$

$$S_I = \cos\theta_I \tag{2}$$

$$S_P = \begin{cases} P > threshold : & 1 \\ otherwise \quad : & 0 \end{cases} \tag{3}$$

3. Actuators

Actuators have a three degree of freedom in rotation, and these are driven according to driving torques which is generated by the controller.

4. Controller

For generating a control signal with a rhythmic pattern, a controller of the virtual creature is modeled by a combination of a central pattern generator (CPG) and an artificial neural network (ANN). A structure of the controller is shown in Fig.5. ANN receives signals from sensors and actuators (see Table2), and it calculate CPG parameters. CPG converts ANN outputs into control signals which have the rhythmic pattern.

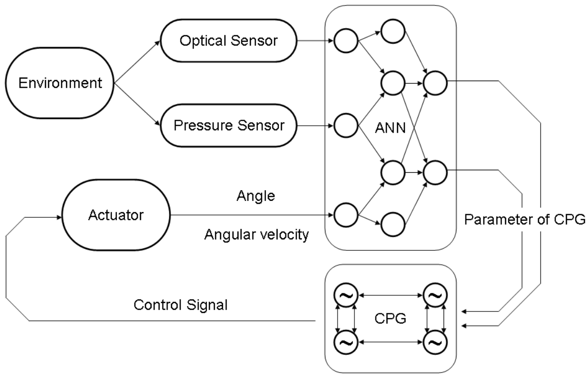


Fig.2. Controller Configuration diagram

Table2. Input signal of ANN

From each sensor	Value
Light strength	$S_L \in [-1, 1]$
Inclination of sensor	$S_I \in [-1, 1]$
Environmental pressure	$S_P \in [0, 1]$
From each actuator	**Value**
Angle	$\cos\theta_A \in [-1, 1]$
Normalized angular velocity	$\omega_A / \omega_{Amax} \in [-1, 1]$

ANN is a well-known brain model. It consists of a set of neurons and set of synapses. Learning of ANN is performed by adjusting a set of weights assigned to synapses. A neuron model of ANN is defined by (4) and (5), where u_i is an input of each neuron, v_i is an output of each neuron, w_{ji} is a synaptic weight, and T is a temperature coefficient. An output of ANN becomes parameters for modifying a CPG output.

$$u_i = \sum_j w_{ji} v_j \tag{4}$$

$$v_i = \frac{1}{e^{-u/T} + 1} \tag{5}$$

CPG is a well-known neural model for generating a rhythmic pattern which is observed in behavior of living organisms [4],[5]. A neuron model of CPG is defined by (6)-(8), where T_r and T_a are coefficients of time response, a_{ij} is a synaptic weight between CPG neurons, g_i is a parameter for modifying an amplitude of output signal, and b_i is a parameter for modifying a frequency of the output signal. CPG parameters are optimized by an optimization algorithm to acquire a periodical signal whose frequency is under 60[Hz] (see Table3). The number of CPG neurons is equals to the total number of degrees of freedom for actuators. Actuators are driven according to output signals from CPG as control torques.

$$T_r \dot{x}_i + x_i = -\sum_j a_{ij} y_j - b_i z_i + g_i \tag{6}$$

$$T_a \dot{z}_i + z_i = y_i \tag{7}$$

$$y_i = \max(0, x_i) \tag{8}$$

Table3. CPG constants

Synaptic weight	a_{ij}=1.070772
Rise time constant	T_r=1.181958
Time lag of the adaptation effect	T_a=0.153337

3. OPTIMIZATION OF CONTROLLER

A salamander's behavior is dominated by the controller. Therefore, adapting the salamander to an environment depends on adjustment of weights assigned to synapses in ANNs and CPGs. This adjustment is so-called learning. However, it is difficult to define learning signals to train controller when the virtual creature has complicated shapes and it virtually lives in the complex environment. For letting the controllers learn, we adopt Genetic Algorithm (GA) with real number encoding. The GA optimizes synaptic weights of ANNs and CPGs. A chromosome is represented by a set of weights. Table4 shows parameters for optimization.

Table4. Parameters for Genetic Algorithm

Number of chromosome	200
Mutation rate	P_M =0.05
Crossover probability	P_C =0.1

The optimization process consists of the following steps.

I. Simulate each virtual creature in a constructed environment according to ANNs and CPGs generated by each chromosome.
II. Evaluate behaviors of each creature by use of a given fitness function.
III. Reproduce new creatures.
IV. Perform GA operations (selection, crossover, and mutation).
V. Return to step II and repeat until the termination condition is satisfied.

The mutation operation randomly selects a chromosome (a set of weights) and extracts a gene (a weight) from it with the mutation rate P_M and replace the gene to a random number [-1.0, 1.0]. The crossover operation selects a couple of chromosomes with the crossover probability P_C and selects one of the output neuron and its neighborhood synapses (which are connected to the selected neuron unit directly). Then these selected synapses of one chromosome are swapped to those of other chromosome.

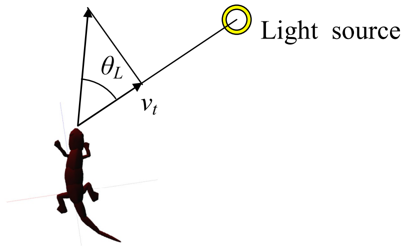


Fig.3. Evaluation values

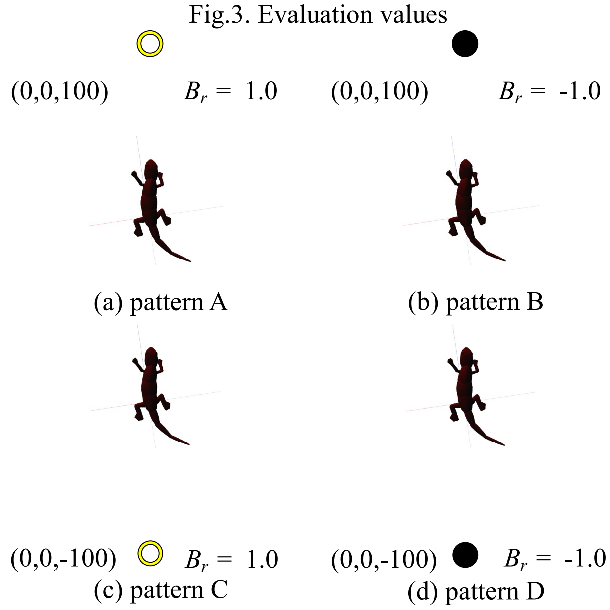


Fig.4. Settings of the Evaluation

We treat a learning problem what behavior a salamander can acquire when it moves towards a given destination and evade from obstacle. It is expected that walking, running, or swimming emerges from the acquired behavior in the given environment.

In this problem, a light source is set in the field as a pheromone (destination or obstacle). All light source can change these brightness B_r within [-1,1]. When the brightness has positive value, we treat it as the destination. Otherwise, we treat it as the obstacle.

A fitness function consists of two fundamental behavior evaluations. The first evaluation is formulated so as to maximize the cumulated propulsive component of velocity V during the salamander moving (see Fig.3). The second one is formulated so as to maximize the cumulated cosine value of the angle between the sensor and the light source L during the salamander moving.

These two evaluations are expressed in (11)-(12), where N_S is the number of sensors.

$$V = \sum_{t}^{step} \sum_{i}^{N_S} v_{t,i} \tag{11}$$

$$L = \sum_{t}^{step} \sum_{i}^{N_S} S_L \tag{12}$$

These values are calculated under four initial positions shown in Fig.4. Therefore, the fitness function (Eq.(13)) is expressed as a cumulated product of Eq.(11) and Eq.(12).

$$f(\vec{V},\vec{L}) = \sum_{p}^{pattern} V_p L_p \qquad (13)$$

4. EVOLVING SALAMANDER BEHAVIOR

Experiments are performed in the following conditions. Basic parameters of experiments are shown in Table 5.

Table5. Parameters for optimization

Time resolution	1/60 [sec]
Simulation time	3000 [step] = 50 [sec]

Each experiment is performed under the different environment described bellow.

1. Acquired behavior on the ground

In the first experiment, the salamander is placed on the ground. Also, the friction and air influence are implemented with the environment.

Fig.5 shows a snapshot of a motion that the salamander moves on the ground after the optimization. The salamander acquires effective motions to reach the goal as fast as possible. The achieved motion looks like a "walk" behavior.

2. Acquired behavior in the water

In the second experiment, the salamander is placed in the water environment.

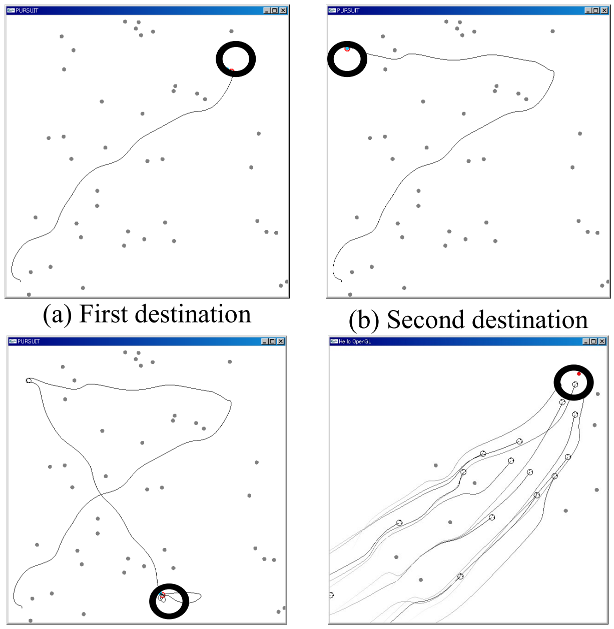
Fig.6 shows a snapshot of a motion that the salamander moves in the water after learning. The controller acquires control signals which cause rapid propagation of vibrations for generating a thrust force by harnessing the water resistance. The achieved motion looks like a "swim" behavior.

3. Behavior emergence in complex environments

Fig.7(a)-(c) show behavior emergence of the virtual creature in the environment with an obstacle. Fig.7(d) shows emergence of a swarm behavior. Each Creature acquires the tracking behavior toward to the destination, and the avoiding behavior from obstacles and other creatures.

Fig.5. An acquired behavior on the ground

Fig.6. An acquired behavior in the water



(a) First destination (b) Second destination

(c) Third destination (d) Swarm behavior

Fig.7. behavior emergence in complex environments

VI. CONCLUSION

We aim at establishing a new computer aided animation method. For this purpose, the agent-based and physics modeling-based animation method is introduced. Numerical experiments proved that the virtual creature acquires effective motions (walking, swimming) to pursuit the destination and to avoid the obstacle and other creatures.

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