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Study on evolution of the artificial flying creature controlled by neuro-evolution

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Abstract: In this paper a flight evolutionary simulation of an artificial flying creature (AFC) is described. The three-dimensional motion of the AFC is calculated by the physical engine PhysX and a numerical expression of the simple drag force. The AFC is controlled by an artificial neural network (ANN). The three-layered ANN which has nine input neurons and four output neurons is used for a simulation of the AFC. To evolve ANNs and to have the AFC flight suitably for given target points, a particle swarm optimization (PSO) optimizes parameters of ANNs. The results of evolutionary simulation show that the ability of generalization does not always increase as evolution progresses, and it depends on given tasks of the AFC. It is also shown that the number of situations which the AFC goes through has positive correlation with the ability of generalization.

Keywords: Artificial life, Artificial neural network, Particle swarm optimization, Neuro-evolution, Physical engine

1 INTRODUCTION

Flight is a complex behavior. A sleeping dog can stay on the ground, while a bird not moving its wings can not stay in the sky. Ants can only move on surfaces, which are commonly regarded as the two-dimensional coordinates. On the other hand butterflies can fly freely in the air, the three-dimensional space. So it is interesting to understand the mechanism of flight, however, there are few researches on them.

Compared with flight, walking, jumping and swimming have been studied by many researchers. Sims [1] simulates evolution of the artificial virtual creatures and shows that creatures can acquire morphology and controllers by evolution with the physical interactions. Lipson et al [2]. and Rieffel et al [3]. also show similar results, however, it is a new point that Rieffel uses PhysX, one of physical engines, for calculating motions. In the field of bipedal walking, Allen et al [4]. and Reil et al [5]. show that bipedal robots can jump or walk through evolution. Wu et al [6]. proposes a bird model for computer graphics. This is one of a few studies on flight behaviors, although the evolutionary acquisition of flight is not done in it.

The objective of this study is to show a process in the evolution of flight behavior. In this paper, we describe a numerical simulation of flight evolution by the use of PhysX and drag force calculation. Although this method can calculate the motion faster, it is approximation and not completely accurate. However, we are focusing on the evolutionary process, and we do not deal with verification of the accuracy by experiments in the real world.

The method used for simulation is described in Section Two. Section Three explains a model of the artificial flying creature and how to evolve its controller by neuro-evolution. Section Four shows the evolutionary simulation and its result. Finally, the conclusion is described in Section Five.

2 COMPUTATIONAL METHOD

In order to calculate motion of the artificial flying creatures, we basically use a physical engine. Because it does not support the force which acts objects in a fluid, we use the simple drag force additionally.

2.1 Physical engine

The physical engine is software used for calculation of the multi body dynamics. The most common purpose of the physical engine is to improve reality in three-dimensional computer graphics. In addition, various types of physical simulations can be done easily by the physical engine, so it is used for researches on artificial-life in recent years.

The physical engine can calculate a motion of the complex object which consists of some objects connected by joints. It can also calculate effects of collision and friction and add force to objects. Since these calculations are automatically performed, the physical engine is regarded as a black box.

2.2 Drag force

Objects in a fluid are affected by the fluid via surfaces of the objects. The physical engine does not support this effect of the fluid yet. We use the simple drag force in order to implement the effect in the physical engine. The drag force D is given by

$$D = \frac{1}{2}\rho C_d A \boldsymbol{v}^2 \qquad (1)$$

where ρ, C_d, A, and $\boldsymbol{v}$ are fluid density, a drag coefficient, an area of a minute surface, and velocity of the surface.

Although this drag force is a kind of the quasi-steady fluid force and a rough approximation, it is fast and easily combined with the physical engine.

3 MODEL OF THE CREATURE

The artificial flying creature (AFC) is controlled by an artificial neural network (ANN). To optimize parameters of ANNs, we use particle swarm optimization (PSO).

3.1 Artificial flying creature (AFC)

3.1.1 Structure

The AFC in Fig. 1. is similar to a bird. It is composed of four parts: a body, a tail, and two wings. The two wings are rotate on the axes $\boldsymbol{e_{R1}}$ and $\boldsymbol{e_{L1}}$, and on the axes $\boldsymbol{e_{R2}}$ and $\boldsymbol{e_{L1}}$. The tail rotates on the axis $\boldsymbol{e_{T1}}$, and on the axis $\boldsymbol{e_{T2}}$. Each rotation is controlled by an output signal of an ANN. To simplify control of the AFC, rotations of two wings are perfectly symmetrical.

3.1.2 Sensors

The AFC has some virtual sensors. They can measure states of the AFC, and perceive cognitive information. They are used as input signals of ANNs.

3.2 Artificial neural network (ANN)

The AFC has a three layered ANN as a controller. The ANN receives eight input signals from virtual sensors: the pitch and roll angles of the AFC, the forward velocity, the relative angles on the axes $\boldsymbol{e_{R1}}$ and $\boldsymbol{e_{R2}}$, the angular velocity on the axis $\boldsymbol{e_{R1}}$, and the angles relative to a target point. Then the ANN calculates four output signals: the angles on the axes $\boldsymbol{e_{R1}}$, $\boldsymbol{e_{R2}}$, $\boldsymbol{e_{T1}}$, and $\boldsymbol{e_{T2}}$.

3.3 Particle swarm optimization (PSO)

In order to optimize ANNs and control the AFC suitably, we use PSO. The PSO is one of the swarm intelligence and has strong convergence. Each position of a particle represents the parameters of an ANN. The position of the particle i at search step k+1, $\boldsymbol{p}^i_{k+1}$, is calculated by

$$\boldsymbol{v}^i{}_{k+1} = w\boldsymbol{v}^i{}_k + c_1 r_1\left(\boldsymbol{p_d}^i{}_k - \boldsymbol{p}^i{}_k\right) + c_2 r_2\left(\boldsymbol{p_g}{}_k - \boldsymbol{p}^i{}_k\right) \qquad (2)$$

and

$$\boldsymbol{p}^i{}_{k+1} = \boldsymbol{p}^i{}_k + \boldsymbol{v}^i{}_{k+1} \qquad (3)$$

where w, c_1, and c_2 are coefficients, r_1 and r_2 are uniform random numbers from 0 to 1. $\boldsymbol{p_d}$ is the best position of the particle i, and $\boldsymbol{p_g}$ is the best of all particles.

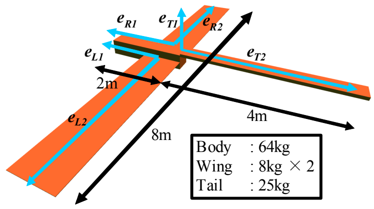

Fig. 1. The artificial flying creature (AFC)

4 EVOLUTION OF FLIGHT TO TARGETS

The AFC evolves to fly to a given target by PSO. We use two different conditions in evolution of the AFC, and then we analyze differences of the process in evolution and the evolved flight to given targets.

4.1 Evolutionary conditions

4.1.1 Common conditions

The AFC is initially placed on the point of (0,200,0) in a static state. Then the AFC starts flying to a target. If the AFC satisfies conditions of termination, the next flight to another target starts, or the next AFC starts flying. The time of numerical integration in PhysX is 1/100 seconds.

We use w = 0.4 and $c_1 = c_2$ = 2.0 as parameters of PSO. We also use 60 particles, and 2000 search steps of PSO.

4.1.2 Conditions in go-and-stay

In the evolution of "go-and-stay", the AFC evolves to go to only one target given by (200,300,200), and stay there. Each AFC flies for 30 seconds, and then it is evaluated by

$$\sum_{t=0}^{3000} \frac{1}{1 + d_t{}^2} \qquad (4)$$

where t and d_t are a time step and a distance from the AFC to the target at time step t.

4.1.3 Conditions in 4-trials

In the evolution of "4-trials", the AFC evolves to go to the four targets given by (200,300,200), (-200,100,200), (-200,300,-200), and (200,100,-200). It does not have to stay around targets. Each AFC flies to a target for 30 seconds at most. If it is situated within 1m from the target, it is considered that the AFC arrives at the target and the flight is terminated. It repeats the flight for a different target four times, and then each is evaluated by

$$\sum_{s=1}^{4}\left\{\sum_{t=0}^{T_s-1}\left(\frac{1}{1 + d_{s,t}{}^2}\right) + \sum_{t=T_s}^{3000} 1\right\} \qquad (5)$$

where s, T_s, and $d_{s,t}$ are the number of trials, a time to arrive at a target in trial s, and a distance from the AFC to the target of trial s at time step t.

4.2 Results of evolution

4.2.1 Changing evaluation in evolution

We have done evolutionary simulations 10 times for go-and-stay and 4-trials. Fig. 2. shows changing evaluations at each search step. The result that differences between the maximum values and average values are larger than one between the minimum values and average values shows high variance of these evolutionary simulations.

4.2.2 Evolved flights

Fig. 3. shows the trajectory and snapshot at every second of the most successful flight given by go-and-stay evolution. In this flight, the AFC goes to the target quickly and flies around the target. This satisfies the aim of "go-and-stay". The number of satisfactory flights, however, is only three. The other flights satisfy only the aim of "go", do not satisfy the aim of "stay".

On the other hand, four different patterns of flight are given by 4-trials evolution. The worst flight is to go back and the AFC falls down. The next worse flight is to go to only one or two targets and the AFC falls down. Two better flights are interesting: one gets low evaluation but fully satisfies "go-and-stay", and the other obtains high evaluation but the AFC falls down after arrival. The arriving rate for (200,300,200), (-200,100,200), (-200,300,-200), and (200,100,-200) are 10%, 40%, 0%, and 70% in ten evolutionary simulations. In even the best flight, the AFC arrives at only two targets given by (-200,100,200) and (200,100,-200).

5 ANALYSYS OF EVOLUTIONARY PROCESS

ANNs have properties of generalization, which is the ability to learn many things by little learning. In the case of the AFC, we have defined the ability of generalization as the ability to reach the targets which are not related to the evaluation of the AFC, and then tested the change of the ability of generalization in evolution.

For tests of generalization, 64 target points are set: 32 points are located on circle-1, and the 32 other points are located on circle-2. The radiuses of circle-1 and circle-2 are $200\sqrt{2}$, and the centers of circle-1 and circle-2 are the points of (0,100,0) and (0,300,0). The length for judgment of arrival is 10m, which is larger than 1m in evolution.

Fig. 4. shows the average values of the successful rate of arrival for 64 targets in evolution. The rate of "4-trials" does not decrease as evolution progresses at least, while that of "go-and-stay" obviously decreases after 500 search steps. This result shows that the evolutionary conditions in go-and-stay are not suitable for increasing generalization.

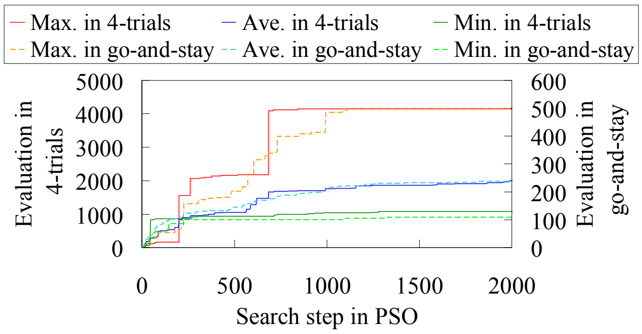

Fig. 2. The change of evaluations in evolution

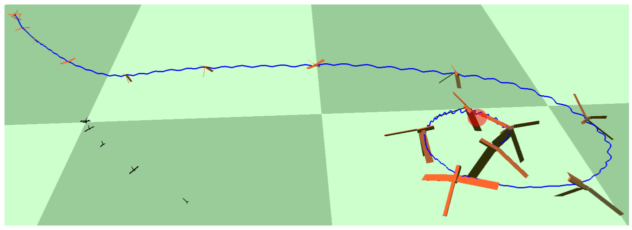

Fig. 3. The most successful flight of go-and-stay

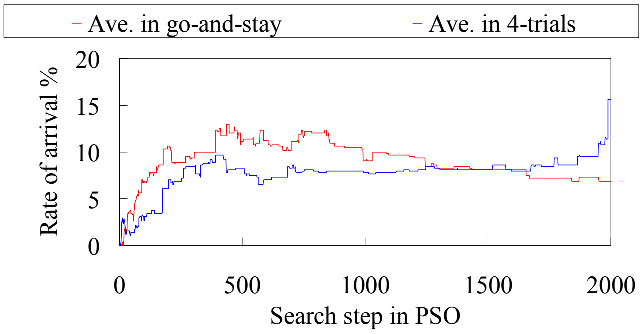

Fig. 4. The successful rate of arrival for 64 targets

We also have counted the "experienced target angles" in evolution of go-and-stay. It is the number of appearing sets of the angles relative to the target in flight. Angles are discretized into integers, and the total number of sets is $360° \times 360° = 129600$.

Fig. 5. shows the relations between the average values of the experienced target angles and the rate of arrival about go-and-stay, and Fig. 6. shows one between the average evaluation and the rate of arrival. Although Fig. 5. shows the relation of monotonic increase, so does not Fig. 6. This result leads us to the idea that increasing the experienced target angles may bring higher successful rate of arrival.

6 EVOLUTION USING TARGET ANGLES

To verify the given hypothesis, we additionally simulate the evolution of the AFC with "experienced target angles". The evolutionary conditions are all the same with that in the evolution of "go-and-stay" but evaluation. The evaluation

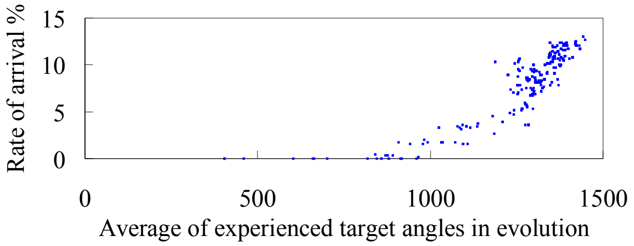

Fig. 5. The relation between the experienced target angles and the rate of arrival in evolution of go-and-stay

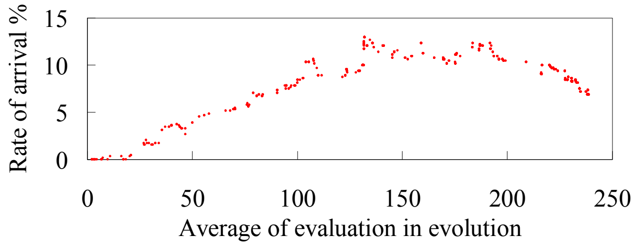

Fig. 6. The relation between the evaluation and the rate of arrival in evolution of go-and-stay

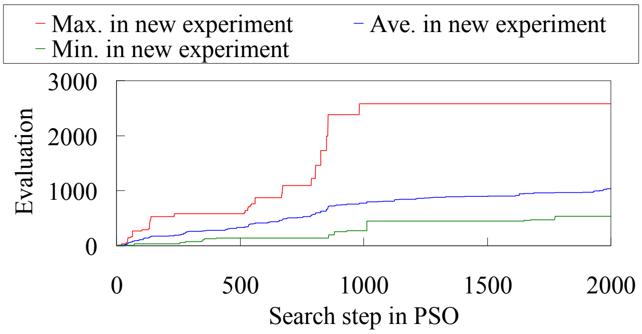

Fig. 7. The change of evaluations in new experiment

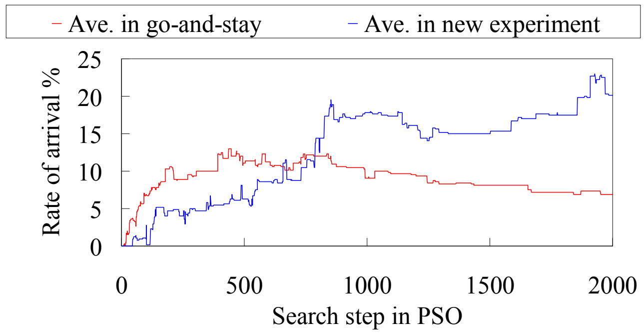

Fig. 8. The successful rate of arrival for 64 targets

of the AFC is given by

$$\left(\sum_{t=0}^{3000} \frac{1}{1+d_t^{\,2}}\right)\left(\frac{100a}{129600}\right)^3 \qquad (6)$$

where a is the number of experienced target angles of the AFC. In short, the AFC which has both the ability of "go-and-stay" and more experiences survives by this evaluation.

Fig. 7. shows average evaluations at each search step given by 10 evolutionary simulations. A high variance between each evolution is similar to one of go-and-stay.

Fig. 8. shows the average values of the successful rate of arrival for 64 targets in evolution. The new experiment brings higher rates of arrival at later search steps, and they roughly show the relation of monotonic increase. This result gives support to our hypothesis.

7 CONCLUSION

We have simulated the evolution of the AFC by using PhysX and the drag force calculation. According to two evolutionary conditions, "go-and-stay" and "4-trials", there are some differences in both the evolved flights and the evolutionary processes. A difference in the successful rate of arrival for 64 targets is the most essential: it increases monotonically in the case of 4-trials, while it decreases as evolution progresses in the case of go-and-stay.

A positive correlation between the rate of arrival and the "experienced target angles" suggests that many experiences about angles for targets keep increasing the rate. The new evolution using experienced target angles verifies this hypothesis, and it also shows that indirect factors influence the ability of generalization in evolution. It is a future work to examine whether our theory applies to other cases or not.

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