A Study on Falling Cat Landing Problem Using Composite Neuroevolution

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Abstract

Cat has ability to safely land in the free fall. In this research, we first construct a virtual cat robot by Physics Modeling. Then we use Composite Neuroevolution to optimize its controller. Composite Neuroevolution optimizes multiple Artificial Neural Networks which are integrated into a complete controller in a pre-defined way. On the contrast, common Neuroevolution algorithms, for example CMA-ES, NEAT, CNE, ESP, optimize one Artificial Neural Network. In our experiment, only Composite Neuroevolution can converge. The result shows the landing behavior is achieved by our method.

Keywords: Cat landing problem, Posture control, Composed behavior, Neuroevolution, Physics Modeling

1. Introduction

A cat has ability to safely land in the free fall. This motion can be regard as two stages. First, the cat rotates itself in the air. Second, the cat keeps balance when landing. The mechanism of rotating lead to a debate, for the conservation law of angular momentum should be kept in the motion. McDonald, Loitsyansky, Kane[1] give different explanations, in which Kane’s explanation is reliable and have been proved by several simulation[2][3].

The previous works[2][3] only provides a 180 degree rotating experiment without controlling legs. We aim at achieving a complex landing behavior which includes both rotating and keeping balance motion. Furthermore, the rotating motion has 5 different initial states. We first construct a virtual cat robot by Physics Modeling. Then we use Composite Neuroevolution to optimize its controller. The result shows the landing behavior is achieved by our method.

2. Virtual Cat Model

We construct our cat model based on Kane’s theory. We use "PhysX (offered by the NVIDIA)” as a physical calculating engine to model and simulate our cat. The Cat robot is composed of a sphere and seven cuboids which represent the head, the tail, four legs, the front part of the body and the back part of the body respectively which are connected by seven joints. Fig.1 shows our model. Actuators are placed on joints at the spine and legs. Their moving range is ±60 degree on two axes as shown in Fig.2.

3. Virtual Cat Controller

The design of controller is subject to our experiment on Neuroevolution which shows optimize controller with one Artificial Neural Network(ANN) is hard to converge when optimizing the rotate behavior. On the contrast, optimizing controller with structure is faster and more successful. The experiment of this conclusion is provided in the next section.

Our controller is composed of three ANNs as shown in Fig.2. They have the same input, but different output. The input is the direction and angular velocity of bodies and legs. Output of working ANN is the signal to control actuators. And output of compose ANN is a priority vector: each priority value is related to a working ANN. The working ANN with the highest priority value is selected to transmit its outputs to the actuators.

4. Composite Neuroevolution

Composite Neuroevolution optimizes a structure which usually composed of several ANN. ANNs are coded one by one in a linear gene and composed in a pre-defined way to create the structure, as shown in Fig.2. To emphasize its advantage, the selection and gene operator are same as CNE. However, it is possible to use other Neuroevolution algorithm like ESP, NEAT or CMA-ES.

5. Convergence problem in rotation behavior

Rotation is the first step to finish the land behavior. However, optimization is hard to converge in this step. To demonstrate it, we compare CMA-ES[4], NEAT[5], CNE[6], ESP[7] and Composite Neuroevolution in this task. We set gravity to 0 and remove legs to simplify the experiment. CNE, ESP, NEAT, CMA-ES only optimize one ANN which is same as working ANN in section 3, and Composite Neuroevolution optimize the entire controller. The hidden neuron is set to 5 for each ANN. Input and output is same as in section 3 except that neurons concerning legs are removed.

The experiment includes 5 different initial states: the cat is rotated 90, 135, 180, 225, 270 degree. Each state simulates for 100 steps. The fitness function for each state is shown in Eq.1. $D_k(\text{part}_k)$ is the distance of direction between denoted part and gravity. $N_k$ is the total simulation steps. $n_k$ is the amount of steps satisfy height < 0.35m. $s_k$ is the last step that satisfy height > 0.35m and $M_k > 0.3$. The total fitness is
\min (f_i^+) \text{ k} \in [0, N_i] \). We accept a convergence if the fitness is greater than 1.8.

\[ MD_i = \max (D_i \text{ (front}, k \text{), } D_i \text{ (back}, k)) \]
\[ f_i^+ = 2 - \min (MD_i) + N_i - n_i - s_i \]
Eq.1

The number of population is 100 for CNE, NEAT, 300 for ESP, 10 for CMA-ES, 50 for Composite Neuroevolution. ALL 5 algorithms can converge if we only consider the performance on one initial state. Fig.3 shows the fitness curves in which the initial state is 180. However, optimizing only one ANN will absolutely fail when consider the performance on all 5 tasks, only Composite Neuroevolution can converge, as shown in Fig.4. This experiment demonstrates the advantage and necessity to use Composite Neuroevolution to optimize the landing behavior.

6 Optimizing landing behavior

We use Composite Neuroevolution to optimize the controller in section 3. Hidden neuron is set to 10 for working ANN and 5 for the compose ANN. The cat is placed at a height of 3m. \( f_i^+ \) is defined to evaluated the ability for keeping balance in Eq.2 and Eq.3, where \( h_t(k) \) is the height of cat at step k.

\[ f_i^+ = \begin{cases} f_i^+_t + 10 \cdot E_i(k_t) & f_i^+ < 2 \\ f_i^+_t & \text{otherwise} \end{cases} \]
Eq.2

\[ E_i = \frac{1}{n_i} \sum h_t(k_i) - \frac{1}{n_i} \sum (h_t(k) - E_t)^2 \]
Eq.3

We define individual A dominate B in Eq.4.

\[ \forall i \in [1,5], f_i^+(A) > f_i^+(B) \text{ and } f_i^+(A) > f_i^+(B) \]
Eq.4

A temporary fitness function is defined as \( F = \min (f_i^+) \).

We first calculated F for each individual and sort them. Then Individuals are sorted based on their amount of dominating individuals. Each individual is assigned to a new F value which has the same sorting index. MDi and heights of body of best individual are shown in Fig.5 and Fig.6. Because each MDi curve is nearly down to 0, and each height curve stops decreasing at nearly 0.15, the cat safely land on the ground. The snapshots are shown in Fig.7.

8 Conclusions

We achieve the cat landing behavior in a five initial states task. The performance of Composite Neuroevolution overcomes common Neuroevolution method in this task. We will study the general ability of this method in the future.

Reference