Couple Particles in Action Space for Reinforcement Learning

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Summary
In this paper, we propose a novel action-search particle-filtering algorithm for learning processes. This algorithm is designed to perform search domain reduction and heuristic space segmentation. In this method, each action space is divided into new two segments using two particles. Appropriate search domain reduction can minimize learning time and enable the recognition of the evolutionary process of learning. In a numerical experiment, the proposed filtering method is applied to a single pendulum simulation in order to demonstrate the adaptability of this simulation model.

Key words:
Reinforcement Learning, TD-Learning, Particle Filter, Single Pendulum Simulation.

1. Introduction
This paper proposes a novel particle-filtering algorithm for reinforcement learning that periodically divides the agent environment and action search space during the learning process. The standard reinforcement learning algorithm [1], [2] requires well-suited segmentation before learning. In the proposed method, each state is searched by the couple particle method, and distance between states are fixed according to the importance of each state. Herein, human-like space segmentation in actor–critic learning, which we investigated previously [3], [4], is further refined. In post-supervised design, clustering, which is done after many trial and error iterations, is a probabilistic method. A genetic algorithm representative of these schemes is called a learning classifier system [5], [6]. In this system, inputted data are encoded as binary rules on which a genetic algorithm alters and selects the best rules. However, inputted data can be encoded during the learning, as in previously investigated method. Our proposed algorithm is applicable not only for reinforcement learning but also for social simulation, which requires each agent to behave rationally during the trial and error iterations. Such an approach provides clues for understanding culture and language.

2. Reinforcement learning
Reinforcement learning assumes that agents can visit only a finite number of states, and that when visiting a state, they will collect a numerical reward (which can be interpreted as a punishment in the case of a negative reward [7]). Each state has a different value associated with it. Given an initial state, subsequent states are reached according to actions. The value of a given state is defined as the average reward that can be collected by selecting actions available in that state.

The actor–critic method includes a critic, which maintains the state value estimate $V$, and the actor, which is responsible for choosing the appropriate action at each state.

Value-function approaches attempt to find a policy that maximizes the return for taken actions by maintaining a set of estimates of expected rewards based on a policy $\pi$. In this method, an agent attempts to estimate the expected reward

$$V(s) = E[R_{t:t+n}] = R_t + \gamma E[R_{t+1:t+n}]$$

where an agent following policy $\pi$ takes an action in state $s$.

In the present paper, we use a normal distribution for the stochastic policy $\pi$. Updating stochastic policy is executed by adjusting output mean $\mu$, rate $\sigma$, and variance $\nu$.

Fig. 1 Actor–Critic method.

Fig. 2 Updating the output by TD-error.
3. Couple particles in each action space

We propose couple particles in the action space. The proposed method using couple particles can search for the global solution (best output) and a local solution, which has the potential of being the global solution. In each state, two particles have expected rewards according to $V(s)$. If inputted data have a positive TD-error, the nearer particle is updated (shown in fig. 3). This method decreases the probability of the local solution.

4. Single pendulum simulation

We simulated the single pendulum standing task (fig. 6). This physical calculation is performed by Runge–Kutta method.

The following motion equation is simulated in increments of 0.05 seconds:

$m\dot{\theta} = -mgl\sin(\pi - \theta) + T + (-\dot{\theta})$

where the parameters and variables are define as

- $m = 1$ kg
- $l = 1$ m
- $k = 0$
- $g = 9.8$ m/s$^2$
- $-\pi < \theta \leq \pi$
- $-3\pi < \dot{\theta} \leq 3\pi$
- $-20 < T \leq 20$
- 1 episode = 5 seconds, 1 learning cycle = 0.2 seconds
- $\theta = \pi, \dot{\theta} = \ddot{\theta} = 0$, in the initial state
- $R = \frac{2m-2k}{4m} - T/40$
- $\alpha = 0.1, \gamma = 0.6$
- variance $\sigma = \frac{1}{2}, \sigma_{loop} = V_o \cdot \sigma_{loop} = 0.0001 \cdot V_o$ for constant $\beta$. 

In addition, because an evenly segmented state is not always good for learning, we also propose adjusting the distance between state prototypes by setting the distance between successive best particles in the output–input space (in fig. 5). This is based on the fact that if the best output is quite different, near states should be searched closely, and otherwise do not need to be. In the process, the updated particle entrains the state particle. Therefore, our proposed method requires that the input and output spaces be normalized.
Figures 7 to 9 show the results of several simulations. The vertical axes in these figures show reward and the horizontal axes show episode times. In each figure, the left panel shows the 100-trial mean of the reward and the right panel shows the best reward. The shown results are for the normal method (blue), our proposed method in which couple particles are applied (green), and our proposed method along with adjusting the distance between state prototypes (red). The agent has 100 states in the learning process. In the simulations shown in fig. 7, each state is segmented evenly. As shown, the proposed method is not always good for learning; however, it does not inhibit the learning process.

In figs. 8 (over segmented δ) and 9 (over segmented δ), the state is not segmented appropriately. As shown, the proposed method leads to be better reward history in terms of speed and value. Our simple segmentation method, especially in the state space, worked very well. Further adjustments in the parameters of the proposed method have the potential of further improving the results.

5. Conclusion

We proposed a novel particle filtering approach to create a novel reinforcement learning algorithm that segments the agent's environment and action. The proposed filtering method is applied to a single pendulum simulation in order to demonstrate the adaptation ability of the model.

Future work

We are implementing this method for a double pendulum simulation.

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References


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