Abstract

Evolutionary Algorithms (EAs) and Deep Reinforcement Learning (DRL) have recently been combined to integrate the advantages of the two solutions for better policy learning. However, in existing hybrid methods, EA is used to directly train the policy network, which will lead to sample inefficiency and unpredictable impact on the policy performance. To better integrate these two approaches and avoid the drawbacks caused by the introduction of EA, we devote ourselves to devising a more efficient and reasonable method of combining EA and DRL. In this paper, we propose Evolutionary Action Selection-Twin Delayed Deep Deterministic Policy Gradient (EAS-TD3), a novel combination of EA and DRL. In EAS, we focus on optimizing the action chosen by the policy network and attempt to obtain high-quality actions to guide policy learning through an evolutionary algorithm. We conduct several experiments on challenging continuous control tasks. The result shows that EAS-TD3 shows superior performance over other state-of-art methods.

1. Introduction

Deep Reinforcement Learning (DRL) has achieved impressive performance in Go (Silver et al., 2016), Atari games (Mnih et al., 2013), and continuous robot control tasks (Lillicrap et al., 2015; Haarnoja et al., 2018). The purpose of DRL is to train an optimal, or nearly-optimal policy network that maximizes the reward function or other user-provided reinforcement signal. Recently, Evolutionary Algorithms (EA) have been applied to the parameter space of neural networks to train policies and showed competitive results as DRL (Salimans et al., 2017; Such et al., 2017).

EA and DRL have complementary properties in training policy networks. On the one hand, EA tends to be good at finding generally good global solutions and might suffer less from local optima than DRL (Majid et al., 2021). However, EA is gradient-free, which leads to its sample inefficiency in training policy networks with millions of parameters. On the other hand, DRL is gradient-based and can use samples to derive gradients to guide the learning of the policy network. Its sample efficiency is higher compared to EA. But DRL sometimes falls into local optimum due to lack of exploration. Dealing with the exploration-exploitation dilemma is one of the intractable problems in DRL.

Given the complementary features of EA and DRL, researchers have attempted to combine the two methods, aiming to exploit the advantages of both to train better policy networks. As one of the pioneers, Khadka & Tumer (2018) proposed Evolutionary Reinforcement Learning (ERL), which has shown promising results in continuous control tasks. As shown in Figure 1a, ERL maintains a population containing n policy networks trained by EA and one policy network trained by DRL. The policy population provides a large number of samples \((s, a, r, s')\) to the RL policy and RL policy will be injected into the population periodically to replace the poorer individual. With the help of EA’s global optimization ability, ERL explores the parameter space of the policy network to search for outstanding parameters. However, taking parameters of the policy network as the target of evolution poses two problems: one is the impact of modifying network parameters is usually unpredictable for the policy performance. The other is the sample inefficiency caused by the introduction of EA. EA searches directly in the high-dimensional parameter space to train the policy network. When faced with a policy network with millions of parameters, EA requires a considerable number of gen-
erations to discover generally good global solutions, which will weaken the sample efficiency of the whole framework. Therefore, ERL requires more timesteps to outperform DRL approaches on continuous control tasks.

These two problems present in ERL are attributed to employing EA to train policy networks. In other words, the target of evolution is the policy network in ERL. Most variants of the ERL (Pourchot & Sigaud, 2019; Khadka et al., 2019; Bodnar et al., 2020; Marchesini et al., 2021) still adopt the policy network as the target of evolution, which will also be subject to the unpredictability and sample inefficiency derived from the usage of EA to train the policy network. In a nutshell, taking the policy network as the target of evolution in ERL will limit the contribution of EA to the learning process, which is contrary to the original intention for better policy learning. Therefore, we wish to explore a more reasonable way to combine EA and DRL, which can not only exploit EA to search for better policies but also avoid drawbacks caused by applying EA to train policy networks.

Our goal is unambiguous, which aims to train a great policy to maximize the cumulative reward of the given task. A great policy \(\mu(a|s)\) means it can choose a good action \(a\) according to the state \(s\) to maximize the cumulative reward. The quality of the action largely determines the quality of the policy. Thus, we intend to take action as the target of evolution. Concretely speaking, as shown in Figure 1b, we use EA to optimize the action chosen by the RL policy, to obtain better evolutionary actions, which can be used to guide the policy learning. The policy network trained by RL collects samples in the environment, and EA extracts actions from samples and evolves better evolutionary actions to guide the RL policy learning. This maintains the flow of information between EA and RL.

Based on the above idea, we propose Evolutionary Action Selection (EAS). EAS uses actions selected by RL policy to form a population and utilizes Particle Swarm Optimization (PSO) (Kennedy & Eberhart, 1995) to evolve the action population from generation to generation. Finally, we get better evolutionary actions, which will be used in the RL policy learning process. We choose PSO for two reasons. Firstly, it has been widely used in many fields and proved to be effective in practice (Wang et al., 2018). Secondly, it is easy to follow and will not add too much computational burden. In addition, PSO can be replaced by other evolutionary algorithms, such as genetic algorithm (Mitchell, 1998), cross entropy method (De Boer et al., 2005), and so on.

The main contributions of this paper are as follows: (1) Combining learning with evolution is a promising direction for both the EA and RL communities. EAS explores a novel combination of the two, which takes action as the target of evolution, rather than the policy network in Evolutionary Reinforcement Learning. (2) Our approach discards the unpredictable effects and inefficiency caused by using EA to train policy networks and brings two benefits. One is the evolutionary target shifts from the parameter space to the low-dimensional action space, which can make good use of the EA’s optimization capability. The other is that EA can utilize samples (here refers to the action in samples) to promote the RL policy learning directly, instead of just providing samples for the RL policy as in ERL. (3) We apply EAS to TD3 (Fujimoto et al., 2018) as EAS-TD3 and conduct a series of empirical studies on a benchmark suite of continuous control tasks to prove the feasibility and superiority of our approach.

2. Related Work

The idea of incorporating learning with evolution has been around for many years (Ackley, 1992; Moriarty et al., 1999; Whiteson, 2006; Grefenstette et al., 2011). With the brilliance of reinforcement learning, recent literature (Gangwani & Peng, 2017; Colas et al., 2018; Marchesini et al., 2021) has begun to revisit the combination of the two to improve the performance of the overall approach.

As mentioned earlier, this paper is related to the recently proposed Evolutionary Reinforcement Learning (ERL) (Khadka & Tumer, 2018) framework. ERL combines Genetic Algorithm (GA) (Mitchell, 1998) with the off-policy DRL algorithm (DDPG) (Casas, 2017) and incorporates the two processes to run concurrently formulating a framework. Specifically, ERL maintains a policy population trained by EA and a policy network trained by RL. By maintaining interactive information flow between EA and RL, the performance of the overall method is promoted. The framework of ERL has triggered a variety of variants, which makes the efficient combination of EA and RL an emerging research direction for both the EA and RL community. Collaborative Evolutionary Reinforcement Learning (CERL) (Khadka et al., 2019) is the follow-up work of ERL. CERL attempts to train multiple policy networks with different hyperparameters to address the DRL’s sensitivity to hyperparameters. Moreover, Proximal Distilled Evolutionary Reinforcement Learning (PDERL) (Bodnar et al., 2020) attempts to figure out the catastrophic forgetting of the neural network caused by the genetic operator used in ERL. CEM-RL (Pourchot & Sigaud, 2019) removes the separate policy network trained by RL and instead allows half of the policy networks in the population to be trained directly by RL and the other half by cross entropy method (CEM) (De Boer et al., 2005). This approach magnifies the impact of gradient-based policy learning methods on the evolutionary population, which improves the sample efficiency of the ERL framework. AES-RL (Lee et al., 2020) proposes an efficient asynchronous method for integrating evolutionary and gradient-based policy search, which shortens the
training time. QD-RL (Cideron et al., 2020) introduces Quality-Diversity (QD) algorithm for RL to address the problem of deceptive reward. Both ERL and our approach aim to integrate the advantages of the EA and DRL for better policy learning. However, we shift the target of evolution from policy networks in ERL to actions and demonstrate empirically that evolving actions is a favorable alternative to evolving policy networks.

In addition to ERL and its variants, our work is related to Derivative-Free Exploration (DFE) (Chen & Yu, 2019), which utilizes a gradient-free approach to optimize the noise of action in policy learning. In DFE, the gradient-free approach revises the action noise which can help promote exploration. However, DFE does not optimize the action itself and does not apply the gradient-free algorithm to promote policy learning. EAS is devoted to combining EA and DRL efficiently. We employ EA to optimize the action chosen by the policy network and exploit the optimized actions to guide the policy learning directly.

3. Methodology

In this section, we present Evolutionary Action Selection and reveal how to optimize action selection of each timestep through PSO. Then, we enable RL policy to learn from evolutionary actions. Finally, we integrate EAS into TD3 as EAS-TD3.

3.1. Fitness Evaluator

PSO requires a fitness evaluator to evaluate the performance of actions in each generation. We hope the action after evolution can obtain a greater expected reward. So the average long-term reward of performing evolutionary actions in the environment appears to be an insightful fitness evaluator. However, this will significantly slow down the evaluation efficiency, which is not what we expect. Therefore, it is decisive to employ a fitness evaluator that can efficiently evaluate the value of each action.

In RL, we use the state-action value function $Q(s,a)$ to represent the long-term reward. $Q(s,a)$ is denoted by Eq. 1, meaning the expected reward the policy $\mu_\theta$ can obtain by performing action $a_t$ in state $s_t$. Once the $Q$ value corresponding to the action is known, we can directly evaluate the expected reward of the action without actually executing it in the environment. Thus, the state-action value function seems to be a more sensible fitness evaluator.

Eq. 2 is a recursive version of Eq. 1, also known as the Bellman expectation equation, which resembles dynamic programming and makes it feasible to estimate $Q$. For specific RL algorithms, a value network is used to estimate the $Q$ function, which is called critic in TD3. Ultimately, we decided to choose the critic network as the fitness evaluator.

The action in population will be input into the critic network to obtain the $Q$ value, whose magnitude can represent the performance of action.

$$Q_{\mu_{\theta}}(s_t, a_t) = \mathbb{E}_{\mu_{\theta}}\left[\sum_{t'=t}^{T} \gamma^{t-t'} r(s_{t'}, a_{t'}) | s_t, a_t \right]$$

$$= \mathbb{E}_{s_{t+1}\sim p} \left[r(s_t, a_t) + \gamma \mathbb{E}_{a_{t+1}\sim \mu_{\theta}}[Q_{\mu_{\theta}}(s_{t+1}, a_{t+1})] \right]$$

3.2. Evolutionary Action Selection (EAS)

The process of EAS is described in pseudocode as shown in Algorithm 1. Taking the critic network $Q_{\mu_{\theta}}$ as the fitness evaluator, EAS follows the process of PSO and evolves the action $a$ chosen by the current policy network $\mu_{\theta}(s)$. The output of EAS is known as the evolutionary action $a^e$, with a higher $Q$ value than action $a$.

In EAS, we first add Gaussian noise to $a$ and make it an action set $A$ containing multiple noisy actions, which serves as the initial population. Actions in the population are also called particles. Secondly, we initialize the velocity vector, which determines the direction and step length when updating actions in the population. Then, we initialize the personal best action set $P = (p_1^b ... p_n^b)$, which records the best solution of each action in the population found so far. The best action in $P$ is called the global best action $g^b$, which represents the best solution found so far. In each generation, action $a_{t}^{gb}$ in the population will be evaluated by fitness evaluator $Q_{\mu_{\theta}}$ to obtain the fitness $Q_{t}^{gb}$. Based on the magnitude of $Q$, we update the personal and global best action. Moreover, the velocity is updated by Eq. 4, which subsequently will be used to update actions and get the next generation of population. In Eq. 4, inertia weight $\omega$ describes that the previous velocity influence on current
velocity. Acceleration coefficients $c_1$ and $c_2$ represent the acceleration weight toward the personal best action and the global best action. $r_1$ and $r_2$ are random variables uniformly distributed in $[0, 1]$. Through several iterations, we can obtain the global best action $g^b$ (denoted as evolutionary action $a^e$). Figure 2 illustrates an intuitive process of the change of global best action $g^b$ step by step. From the first to the last iteration, we record the action with the highest $Q$ value found so far. Eventually, the initial action $a$ chosen by the policy (the red mark) becomes the evolutionary action $a^e$ (the blue mark) after EAS. The relationship of $Q$ between $a^e$ and $a$ is:

$$Q_{\mu_b}(s, a^e) \geq Q_{\mu_b}(s, a)$$

(3)

which reveals that EAS can increase the $Q$ value of the action so that the action will have a higher expected reward. We claim the changing from $a$ to $a^e$ is the action evolution. The evolutionary action $a^e$ is better than $a$ and has a higher expected reward.

**Algorithm 1 Evolutionary Action Selection**

**Input:** State $s$, action $a$, critic network $Q_{\mu_b}$  
**PSO parameters:** Inertia weight $\omega$, acceleration coefficients $c_1$, $c_2$, random coefficients $r_1$, $r_2$  
**Output:** Evolutionary action $a^e$  

1. Extend the action $a$ with Gaussian noise $\epsilon$ to form the initial action population $A = (a_1, a_2, \ldots, a_N)$, $a_n = a + \epsilon_n, \epsilon \sim N(0, \sigma), N$ is the number of actions  
2. Initialize the velocity of action $V = (v_1, v_2, \ldots, v_N)$, $|v_n| = |a_n| = D, v_n \in [-v_{max}, v_{max}]$  
3. Initialize personal best action set $P = (p^1, p^2, \ldots, p^N)$ and global best action $g^b$  
4. for $t = 1$ to $T$ do  
5. for $n = 1$ to $N$ do  
6. $Q^t_n \leftarrow Q_{\mu_b}(s, a^t_n)$  
7. // Update the personal and global best action  
   $p^b_n \leftarrow a^t_n; \text{ if } Q^t_n > Q_{p^b_n}$  
   $g^b \leftarrow p^b_n; \text{ if } Q_{p^b_n} > Q_{g^b}$  
8. // Update the velocity  
   $v_{n+1} = \omega * v_n + c_1 * r_1 * (p^b_n - a^t_n)$  
   $+ c_2 * r_2 * (g^b - a^t_n)$

(4)

9. // Update the action  
   $a^{t+1}_n = a^t_n + v_{n+1}^{t+1}$

(5)

10. end for  
11. end for  
12. Obtain the global best action $g^b$, representing evolutionary action $a^e$

### 3.3. Learn from Evolutionary Action

Through EAS, we obtain evolutionary actions, storing their corresponding state-action pairs $(s, a^e)$ into an archive $A$. As mentioned earlier, the evolutionary action has a higher expected reward than the original action. Consequently, we intend to make the action space of RL policy similar to the space of evolutionary actions so that the evolutionary actions can contribute to the RL policy learning. Due to the idea given above, we construct a loss as below:

$$L_{evo}(\theta, A) = \mathbb{E}_{(s, a^e)} \sim A \left[ \| \mu_b(s) - a^e \| \right]^2$$

(6)

where $s_i$ and $a^e_i$ represent the state and evolutionary action from $A$ respectively, and $\theta$ represents the learning parameters in RL policy $\mu_b$. We call $L_{evo}$ evolutionary action gradient. Furthermore, we weigh the constructed loss with an extra $Q_{filter}$ as proposed in Nair et al. (2018):

$$Q_{filter} = \begin{cases} 1, & \text{if } Q_{\mu_b}(s, a^e) > Q_{\mu_b}(s, \mu_b(s)), \\ 0, & \text{else.} \end{cases}$$

(7)

The purpose of $Q_{filter}$ is to drop out $L_{evo}(\theta, A)$ when the action chosen by the current RL policy is superior to the evolutionary action. The reason is that if an evolutionary action generated a long time ago is sampled to update parameters, the action chosen by the current policy may be better than the previous evolutionary action. Thus, we need to filter out those outdated evolutionary actions. We periodically draw a few mini-batches of state-action pairs from $A$ and utilize Eq. 8 to update parameters.

$$\nabla_{\theta} L_{Q_{filter,evo}} = Q_{filter} \nabla_{\theta} L_{evo}$$

(8)

### 3.4. EAS-TD3 Framework

EAS promotes the evolution of actions, which can be used to guide strategy learning. The introduction of $Q_{filter}$ effectively avoids a poor direction for learning when the action chosen by the current policy is superior to the previous evolutionary action. We refer to the dual integration with TD3 as Evolutionary Action Selection Twin Delayed Deep Deterministic Policy Gradients (EAS-TD3). Figure 3 illustrates a diagram of EAS-TD3.

At each timestep $t$, the policy observes $s_t$ and outputs action $a_t$. Then, we receive a reward $r_t$ and environment transitions to next state $s_{t+1}$. These four elements make up the sample $(s_t, a_t, r_t, s_{t+1})$, which will be stored into the replay buffer $R$. Then, EAS performs evolution on action $a$ to obtain evolutionary action $a^e$, which will be stored into an archive $A$. We draw the same mini-batches from $R$ and $A$ and update the current policy $\mu_b$ with Deterministic Policy Gradient (Silver et al., 2014) and $L_{Q_{filter,evo}}$. EAS adopts the way of delayed policy updates: one policy update for two $Q$ function updates, which is the same as TD3.
In addition, the capacity of archive $A$ is generally not large, in that the policy will continue to learn while evolutionary action selection is based on the policy at that time. Therefore, we should control the size of $A$ to keep evolutionary actions fresh. Otherwise, the previous evolutionary actions will not play a role in guiding policy learning. In section 4.4, we explore the impact of different archive sizes.

All hyperparameters for TD3 are the same as those in the original paper (Fujimoto et al., 2018) by default. Here, we just provide the unique hyper-parameters of the EAS-TD3. With regard to PSO, inertia weight $\omega$ is 1.2, acceleration coefficients $c_1, c_2$ are both 1.5, the number of iterations $T$ is 10, $v_{\text{max}}$ is 0.1, random coefficients $r_1, r_2$ are random numbers from 0 to 1. The size of archive $A$ is 100000 for all environments. $N$ is 10, which represents the action population size. More details about parameters can be found in Appendix C.1, which contains all hyperparameter settings and descriptions.

Our method is compared against the official implementations for TD3 (S.Fujimoto, 2018), CEM-TD3 (based on TD3) (Pourchot & Sigaud, 2019), CERL (based on TD3) (Khadka et al., 2019), PDERL (based on DDPG) (Bodnar et al., 2020), ERL (based on DDPG) (Khadka & Tumer, 2018). These baselines contain a series of studies on the combination of EA and RL.

4.2. Performance Comparison

Figure 4 demonstrates the reward curves in MuJoCo and Bullet environments. In general, EAS-TD3 performs consistently well across most environments, indicating that the newly introduced mechanism plays a significant role in the process of policy learning.

**Compared to ERL and its variants.** EAS-TD3 performs a large improvement on high state and action dimension environments like Humanoid, Ant, Walker2d, AntBullet. The reason is that the parameters of the policy network are associated with the state and action dimensions of the environment. For environments with higher dimensions, their policy networks also have more parameters, and more timesteps are needed for EA to search for good policies. For example, a policy network in Ant-v3 consisting of two hidden layers with 400 and 300 nodes will have more than 150000 parameters, which takes more timesteps to learn a decent policy for gradient-free evolutionary methods. So the learning speed of ERL and its variants is slower than EAS-TD3 and TD3 in the early stage.

In CEM-TD3, CERL, PDERL, and ERL, there are multiple policy networks trained by EA, which will weaken the sample efficiency of the framework. CEM-TD3 benefits from the fact that half of the policy networks in the population are trained directly by RL, which will enhance the sample efficiency of the method. Therefore, CEM-TD3 performs the best among ERL and its variants. However, since the other half of the policy networks in the population are still trained by the cross entropy method (CEM) (De Boer et al., 2005), it may lead to unpredictable impact and inefficiency due to EA training policy networks as mentioned before. Thus, the sample efficiency of CEM-TD3 is still not as good as EAS-TD3, and even weaker than TD3. EAS-TD3 significantly

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**Figure 3.** A high-level view of EAS-TD3. RL policy interacts with the environment to generate the sample $(s, a, r, s')$, which will be stored in a replay buffer. Action $a$ is added with Gaussian noise to form an evolutionary population. Then use EAS to update the action population to obtain the evolutionary action $a^*$. The state-action pair $(s, a^*)$ will be stored in an archive. We draw minibatches from the replay buffer and archive to update the current RL policy with policy gradient and evolutionary action gradient.

**Figure 4.** demonstrates the reward curves in MuJoCo and Bullet environments. In general, EAS-TD3 performs consistently well across most environments, indicating that the newly introduced mechanism plays a significant role in the process of policy learning.

4. Experiment

The main purpose of this section is to investigate the mechanism of EAS and the performance of EAS-TD3 compared to other evolutionary reinforcement learning methods. We conduct experiments on the continuous locomotion tasks from MuJoCo and Bullet.

4.1. Experimental Setup

We select five continuous control locomotion tasks from OpenAI Gym (Brockman et al., 2016) simulated by MuJoCo (Todorov et al., 2012): HalfCheetah-v3, Hopper-v3, Walker2d-v3, Ant-v3, Humanoid-v3 and two from PyBullet Gym simulated by Bullet (Coumans & Bai, 2016–2021): Walker2DBulletEnv-v0, AntBulletEnv-v0. The state and action dimensions of these tasks are detailed in Table 1. Notably, the Bullet locomotion environments are derived from Roboschool (Schulman et al., 2017) and are harder than default MuJoCo versions. We present the average reward and the associated standard deviation over 10 runs with random seeds 0-9. For each run, we test the learning policy on 10 evaluation episodes every 5000 steps. In all figures of learning curves, unless specified otherwise, the x-axis represents the number of steps performed in the environment and the y-axis represents the mean return obtained by the policy.
Table 1. The state and action dimensions of all environments. W2DBullet refers to Walker2DBullet.

| Environment            | Ant | HalfCheetah | Walker2d | Hopper | Humanoid | AntBullet | W2DBullet |
|------------------------|-----|-------------|----------|--------|----------|-----------|-----------|
| State Dimension        | 111 | 17          | 17       | 11     | 376      | 28        | 22        |
| Action Dimension       | 8   | 6           | 6        | 3      | 17       | 8         | 6         |

Figure 4. The learning curves in MuJoCo and Bullet environments. The shaded area represents mean ± standard deviation over the 10 runs.

outperforms CEM-TD3 in high-dimensional environments such as Ant, Humanoid, AntBulletEnv, Walker2DBulletEnv, which confirms the effectiveness of EAS. Besides, the ERL and its variants report the average performance of all policy networks in the population, which is the advantage of the policy population and makes the learning process stable.

**Compared to TD3.** As shown in Figure 4, EAS-TD3 outperforms TD3 in almost all environments. Compared with TD3, the increment of EAS-TD3 only lies in the influence of evolutionary action gradient, which indicates the performance enhancement does come from the introduction of EAS. What’s more, EAS uses the same set of hyperparameters for all environments as mentioned before, which demonstrates that EAS is hyper-parameter insensitive and can guide the policy learning for different tasks. In HalfCheetah, EAS-TD3 achieves a minor improvement in experiments with multiple random seeds. Since TD3 has already shown promising results in this environment, the evolutionary action can slightly enhance the sampling efficiency and performance. At the same time, EAS-TD3 performs well in high-dimensional difficult tasks environments such as Ant, Walker2d, and Humanoid, as the gradient of evolutionary action rapidly drives the policy’s action space toward regions with higher expected reward and greatly improve learning speed and final performance.

4.3. Performance on Delayed Environment

To further explore the role of evolutionary action as guidance for policy learning, we conduct experiments on continuous control tasks with delayed reward signals. Specifically, we modified tasks in OpenAI gym to give a delayed cumulative reward only after every \( N \) step (or when the episode terminates). \( N \) is 20 for Walker2d and HalfCheetah and 10 for Ant and Humanoid. As the reward signal becomes sparse, the learning ability of RL algorithms will be weakened. However, EA is less affected by the sparsity of the reward, in that EA does not utilize single-step rewards as the fitness function but uses the cumulative rewards over an episode (for ERL and its variants) or \( Q \) values (for EAS). Therefore, in delayed reward environments, the contribution of EA to policy learning becomes increasingly important. Figure 5 shows the learning curves in Delayed environments. EAS-TD3 outperforms TD3 in all environments, which indicates that evolutionary actions, even in delayed reward environments, can also play a good role in promoting policy learning. Comparing ERL and its variants, EAS-TD3 outperforms all methods in most environments except for Delayed HalfCheetah-v3. It further confirms the superiority of our hybrid approach. In conclusion, the policy can benefit from the promotion of evolutionary actions and exhibit better performance in both dense and delayed environments.
4.4. Ablation Studies

The size of archive $A$. We select different archive sizes (10000, 50000, 100000, 500000) and perform an ablation study on the size of $A$. As shown in Figure 6a and 6b, the archive size affects the performance. $A$ stores state-action pairs $(s, a')$ corresponding to evolutionary actions. Since the evolutionary actions are evolved based on actions chosen by the current policy, the archive size shouldn’t be too large. Otherwise, $A$ will store outdated actions, which may weaken the role of evolutionary action. In contrast, it shouldn’t be too small, or the diversity of actions in $A$ may be poor. This will lead to the frequent sampling of limited evolutionary actions and hinder the exploration ability of policy. From Figure 6, 100000 seems to be a reasonable size for these tasks.

The effect of $Q$ filter. $Q$ filter is employed to prevent adding evolutionary action gradient when the action chosen by the current policy is better than the evolutionary action. Since RL policy is constantly learning and improving, previous evolutionary actions may be inferior to actions chosen by the current policy. Figure 6c and 6d show the influence of $Q$ filter. Without $Q$ filter, the learning process of HalfCheetah will be affected by the obsolescence of evolutionary actions, which will weaken the performance. We also found that in a high-dimensional environment like Ant, even without $Q$ filter, it can also achieve good performance. It’s because the appropriate size of the archive plays a role. The evolutionary actions in the archive are kept fresh and are well used to guide strategy learning.

4.5. Evolutionary Action Evaluation

In this section, we will reveal the mechanism of EAS and mainly answer a question: how do evolutionary actions promote policy learning?

Figure 7 shows the first two-dimensional distributions of actions chosen by the policy and the corresponding evolutionary actions during the training process of Walker2d-v3. Each plot demonstrates the distribution of all actions in every 100000 timesteps. The performance of the policy will gradually improve over timesteps. Therefore, the action distribution plot of each column in Figure 7 indicates a higher expected reward than the previous column. We can see that evolutionary actions predict the action space with higher expected reward in advance and guide the current policy to move towards there, which may explain why EAS works. For example, within the 0 to 100,000 timesteps (corresponding to the two plots in the first column), the distribution of the evolutionary action exhibits a trend from the upper right downward. The downward trend subsequently becomes more pronounced. Correspondingly, the policy action distribution shows the same trend under the guidance of both policy gradient and evolutionary action gradient. This indicates that evolutionary action gradient and policy gradient promote learning of the policy network in the same direction, which significantly accelerates the progress of policy learning. From Figure 7, we also discover that the space of evolutionary actions doesn’t deviate too much from the current policy’s action space, which is served as a gentle mentor and guides the current policy step by step. See Appendix C.3 for a complete distribution and more analysis.

In addition, we recorded the $Q$ values of each action and the
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Figure 7. This plot shows the distribution of the first two action dimensions during the training process. The red contour represents the current policy’s actions and the blue contour represents the corresponding evolutionary actions. The performance of the policy will gradually improve over timesteps. The action distribution plot of each column indicates a higher expected reward than the previous column. Evolutionary actions predict the action space with a higher expected reward in advance and guide the current policy to move towards there.

Figure 8. Increase of $Q$ value by EAS. In the training process, the growth of $Q$ value by EAS increases gradually and tends to be stable.

corresponding evolutionary action throughout the training process. Figure 8 demonstrates the magnitude of the $Q$ value growth before and after the action evolution. In the training process, the growth of $Q$ value increases gradually and tends to be stable, which reveals EAS can provide long-term and stable guidance for the whole learning process. Besides, in the period when the learning curve rises rapidly (200000 to 600000 timesteps), the growth of $Q$ value is also large. Especially in the Humanoid environment, the learning curve rises fastest at 300000 to 400000 timesteps while the $Q$ value growth is also greatest, which reveals that the performance improvement does come from EAS. In conclusion, with the aid of evolutionary action gradient, we can make good use of evolutionary actions and finally play a role in the learning process.

5. Conclusion and Further Work

This paper proposes a mechanism for incorporating learning with evolution called Evolutionary Action Selection, which can apply evolution for the action chosen by the policy. Compared with other hybrid methods, our approach transforms the target of evolution from the policy network in ERL to the action and explores a novel way of combining EA and DRL. A series of empirical studies have revealed that our approach can exploit EA to search for better policies and avoid the unpredictable effects and inefficiency caused by the introduction of EA. In addition, we also analyze how evolutionary actions promote policy learning. With the guidance of evolutionary actions, we train policies that substantially outperform those trained directly by TD3 and other compared methods in several continuous control tasks. Besides, EAS may be applied to discrete action space, which can evolve the softmax output of the policy network.

Going forward, combining learning with evolution is a promising direction. We believe that our work can trigger follow-up studies to address several interesting open questions. As future work, we can integrate the idea of Quality-Diversity (QD) (Cully et al., 2015; Pugh et al., 2016), which not only evolve high-quality actions but also evolve diverse actions to deal with the environment with deceptive rewards. Moreover, we can evolve different types of actions for different environments to help transfer one policy to multiple tasks.
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Evolutionary Action Selection for Gradient-based Policy Learning
Appendix

A. Background

A.1. Twin Delayed DDPG (TD3)

The general off-policy RL method is Deep Deterministic Policy Gradient (DDPG) (Casas, 2017), which is developed for handling the case of high-dimensional continuous action space. Fujimoto et al. (2018) extended DDPG to Twin Delayed DDPG (TD3). With a significant improvement upon DDPG, TD3 is a state-of-the-art off-policy algorithm for RL in continuous action spaces. TD3 uses an actor-critic architecture and maintains a deterministic policy (actor) \( \pi : S \rightarrow A \), and two independent action-value function approximations (critics) \( Q : S \times A \rightarrow Q(s, a) \). Generated by the actor performing the action \( a \), the experience \( (s_t, a_t, r_t, s_{t+1}) \) is saved into a replay buffer \( R \) thereafter. Actor and critic networks are updated by randomly sampling mini-batch from \( R \). Critic is trained by minimizing the MSE loss function:

\[
L = N^{-1} \sum (y - Q_{\theta_i}(s, a))^2
\]

where \( y = r + \gamma \min_{i=1,2} Q_{\theta_i}(s', \tilde{a}) \) (9)

\( \tilde{a} \) is the noisy action computed by adding Gaussian noise. TD3 adds noise to the target action. Actor is trained by deterministic policy gradient (Silver et al., 2014):

\[
\nabla_{\theta} J(\theta) = N^{-1} \sum \nabla_{a} Q_{\theta_i}(s, a)|_{a=\pi_{\theta}(s)} \nabla_{\theta} \pi_{\theta}(s)
\] (10)

A.2. Particle Swarm Optimization

PSO (Kennedy & Eberhart, 1995) is a meta-heuristic global optimization paradigm whose basic concept originated from the study of bird flocks foraging behavior. It has turned out to be successful in dealing with diverse problems such as image segmentation (Omran et al., 2006; Mohsen et al., 2012), hyperparameter selection (Ye, 2017; Lorenzo et al., 2017) and natural language processing (Tambouratzis, 2016; Zang et al., 2019). Hassan et al. (2005) has claimed the proof of equal effectiveness but superior efficiency for PSO over the Genetic Algorithm (GA) (Mitchell, 1998). PSO uses a population to explore the optimal solution of the \( D \)-dimensional search space. This population is called a swarm, which contains multiple individuals called particles. Each particle has only two specified attributes: position and velocity. One represents the current position in the search space, while the other represents the direction of movement.
B. Implementation Details

B.1. Evolution Action Selection Details

Figure 9 illustrates the intuitive process of Evolutionary Action Selection. Add Gaussian noise to the action chosen by the policy and form the initial population. The Gaussian noise we add is generally the white noise \( N(0, 1) \). As the fitness evaluator, the critic network is used to generate \( Q \) values for each generation of the action population, from where we update the individual best action \( p^b \) and global best action \( g^b \). Then, we update the action \( a_n \) and the velocity \( v_n \). After several generations, the global best action \( g^b \) will be served as the evolutionary action \( a^e \).

![Figure 9. The framework of Evolutionary Action Selection.](image)

B.2. EAS-TD3 Pseudocode

**Algorithm 2 EAS-TD3**

```plaintext
1: Initialize policy networks \( \mu_\theta \), critic networks, \( Q_{\mu_\theta 1}, Q_{\mu_\theta 2} \) with random parameters.
2: Initialize Archive \( A \), Replay Buffer \( R \)
3: for \( t = 1 \) to total_steps do
4:     Policy \( \mu_\theta \) chooses an action \( a_t \) based on the current state \( s_t \)
5:     Execute action \( a_t \), obtain reward \( r_t \), next state \( s_{t+1} \), terminal flag \( d \)
6:     Store sample tuple \( (s_t, a_t, r_t, s_{t+1}, d) \) in Buffer \( R \).
7:     Utilizing EAS to evolve action \( a_t \), and obtain evolutionary action \( a^e \)
8:     Store state-action pair \( (s_t, a^e) \) in Archive \( A \)
9:     Sample a mini-batch samples \( (s, a, r, s', d) \) from Buffer \( R \)
10:    Policy \( \mu_\theta \) choose next action \( a' \) based on next state \( s' \)
11:    \( Q(s', a') \leftarrow \min_{j=1,2}(Q_{\mu_\theta j}(s', a')) \)
12:    \( y \leftarrow r + \gamma(1-d)Q(s', a') \)
13:    Update the critic \( Q_{\mu_\theta 1}, Q_{\mu_\theta 2} \) according to Bellman loss Eq.9
14:   if \( t \% 2 == 0 \) then
15:       Update the policy \( \mu_\theta \) according to policy gradient Eq.10
16:       Sample a mini-batch state-action pairs \( (s, a^e) \) from Archive \( A \)
17:       Update the policy \( \mu_\theta \) according to evolutionary action gradient Eq.8
18:   end if
19: end for
```
C. Experimental Details

C.1. Hyperparameters

Hyperparameters of TD3 and EAS are detailed in Table 2. In addition, for Delayed MuJoCo environment, we adjust the learning rate. For the Delayed Walker2d and Delayed Halfccheat, the learning rate is still 1e-3. For Delayed Ant, the learning rate is 7e-5, and for Delayed Humanoid, the learning rate is 1e-4.

| Hyperparameter                     | All environments except for Humanoid-v3 | Humanoid-v3 |
|------------------------------------|----------------------------------------|-------------|
| **Hyperparameters for TD3**        |                                        |             |
| Batch size                         | 100                                    | 256         |
| Policy network                     | (400,300)                              | (256,256)   |
| Critic network                     | (400,300)                              | (256,256)   |
| Learning rate                      | 1e-3                                   | 3e-4        |
| Optimizer                          | Adam                                   |             |
| Replay buffer size                 | 1e6                                    |             |
| Start timesteps                    | 2.5e4                                  |             |
| Exploration noise                  | \(N(0, 0.1)\)                          |             |
| Discount factor                    | 0.99                                   |             |
| Target update rate                 | 5e-3                                   |             |
| Noise clip                         | 0.5                                    |             |
| Policy update freq                 | 2                                      |             |
| **Hyperparameters for EAS**        |                                        |             |
| Archive size                       | 1e5                                    |             |
| Population size \(N\)              | 10                                     |             |
| Inertia weight \(\omega\)          | 1.2                                    |             |
| Acceleration coefficients \(c_1\)  | 1.5                                    |             |
| Acceleration coefficients \(c_2\)  | 1.5                                    |             |
| Random coefficients \(r_1\)        | \(\text{rand}(0, 1)\)                  |             |
| Random coefficients \(r_2\)        | \(\text{rand}(0, 1)\)                  |             |
| Iteration number                   | 10                                     |             |
| Maximum velocity \(v_{\text{max}}\)| 0.1                                    |             |

- **Archive size = 100000**
  Archive size stores state-action pairs \((s, a^c)\) corresponding to evolutionary actions. As shown in the ablation study, this parameter should not be too large or too small. This parameter should not be too large or too small, which is usually set to one-tenth of the replay buffer size.

- **Population size \(N = 10\)**
  Population size represents the number of actions in the population. A large number allows each iteration to cover a larger search space. However, more particles will increase the computational complexity of each iteration and the search may degenerate to a parallel random search. 10 is a moderate value.

- **Inertia weight \(\omega = 1.2\)**
  Inertia weight is used in the Eq. 4 for velocity update. Velocity determines the direction and magnitude of the action update. Inertia weight describes the influence of the previous generation’s velocity on the current generation’s velocity, which is usually set to between 0.8 and 1.2. If \(\omega\) is large, the global optimization ability is strong, and the local optimization ability is weak. On the contrary, the local optimization ability is strong.

- **Acceleration coefficients \(c_1 = 1.5, c_2 = 1.5\) and random coefficients \(r_1 = \text{rand}(0, 1), r_2 = \text{rand}(0, 1)\)**
  According to Eq. 4, acceleration coefficients \(c_1\) and \(c_2\), together with random coefficients \(r_1\) and \(r_2\), control the stochastic influence of individual optimal action \(p^b\) and global optimal action \(g^b\) on the current generation’s velocity. \(c_1\) and \(c_2\) are also referred to as trust parameters, where \(c_1\) expresses how confident the current action trusts itself while \(c_2\)
expresses how confident the current action trusts the population (Clerc, 2010). According to empirical studies, $c_1$, $c_2$ are generally set between 0.5 and 2.5.

- **Iteration number = 10**
  Iteration number represents the number of generations of the action population.

- **Maximum velocity $v_{max} = 0.1$**
  $v_{max}$ represents the maximum velocity of each action in the population, which is generally set to one tenth of the maximum value of the action.

### C.2. Further Studies on Fitness Evaluator

During the training process, both the critic network and the policy network gradually get better. Eventually, the critic network can accurately evaluate the \( Q \) values of actions. The policy network can output high-quality actions to obtain higher cumulative rewards. It is a common bootstrap learning process in RL.

As mentioned earlier, we regard the value network in RL (called critic network in TD3) as a fitness evaluator to evaluate the fitness of each action in the population. Therefore, in the early stage of training, the evaluation of the \( Q \) value is relatively inaccurate, which may weaken the quality of evolutionary actions. So a question then arises. If a relatively perfect fitness evaluator is available during the training process, will evolutionary actions have greater facilitation on the policy learning? We devised a new variant of the EAS-TD3 called *PretrainedCritic-EAS-TD3*. We use TD3 to pretrain a critic network (one million timesteps) as the fitness evaluator of EAS, whose parameters will be frozen during the training process. Figure 10a, 10b show the learning curves. It can be seen that the pretrained fitness evaluator can make evolutionary actions further promote policy learning. Therefore, the pretrained critic network might be an alternative for the fitness evaluator, and how to devise the fitness evaluator will be an interesting follow-up work.

![Figure 10](image)

*Figure 10. Experiments (mean ± standard deviation) on pretrained fitness evaluator.*

### C.3. Further Evaluation on Evolutionary Action

Figure 11, 12, 13 display the distribution of actions chosen by the policy and corresponding evolutionary actions during the training process of Walker2d-v3 (from dimension 0 to dimension 5). For presentation purposes, we rotate the figure to the vertical. Each row represents the action space of every 100000 timesteps. In other words, we store all the actions chosen by the policy during training and the corresponding evolutionary actions and plot the distribution of the actions every 100,000 timesteps. The red contour represents the current policy’s actions and the blue contour represents the corresponding evolutionary actions.

The performance of the policy will gradually improve over timesteps. Therefore, the action distribution plot of each row in the figures indicates a higher expected reward than the previous row. In Figure 11, we can see the evolutionary actions (the blue plot) show a trend of aggregation in the upper right corner at 500000 to 600000 timesteps. Then the action distribution of the policy (the red plot) gradually showed the same trend guided by evolutionary actions. The same situation occurs in Figure 13, where evolutionary actions (the blue plot) show a trend of extending from the lower right to the left at 100000 to 200000 timesteps. Then the action of the policy (the red plot) gradually showed the same trend. In short, evolutionary actions will predict the action space with a higher expected reward in advance and guide the current policy to move towards there. Policy gradient and evolutionary gradient promote strategy learning in the same direction, ultimately improving the sample efficiency and the final performance.
Figure 11. The zeroth and first dimensional distribution of the action in Walker2d-v3. The red contour represents the current policy’s actions and the blue contour represents the evolutionary actions.
Figure 12. The second and third dimensional distribution of the action in Walker2d-v3. The red contour represents the current policy's actions and the blue contour represents the evolutionary actions.
Figure 13. The fourth and fifth dimensional distribution of the action in Walker2d-v3. The red contour represents the current policy’s actions and the blue contour represents the evolutionary actions.