Optimal Actor-Critic Policy With Optimized Training Datasets

Chayan Banerjee, Zhiyong Chen, Senior Member, IEEE, Nasimul Noman, Member, IEEE, and Mohsen Zamani, Senior Member, IEEE

Abstract—Actor-critic (AC) algorithms are known for their efficacy and high performance in solving reinforcement learning problems, but they also suffer from low sampling efficiency. An AC based policy optimization process is iterative and needs to access the agent-environment to evaluate and update the policy by rolling out the policy, collecting rewards and states (i.e., samples), and learning from them. It ultimately requires a huge number of samples to learn an optimal policy. To improve sampling efficiency, we propose a strategy to optimize the training dataset that contains significantly less samples collected from the AC process. The dataset optimization is made of a best episode only operation, a policy parameter-fitness model, and a genetic algorithm module. The optimal policy network trained by the optimized training dataset exhibits superior performance compared to many contemporary AC algorithms in controlling autonomous dynamical systems. Evaluation on standard benchmarks shows that the method improves sampling efficiency, ensures faster convergence to optima, and is more data-efficient than its counterparts.

Index Terms—Actor critic, reinforcement learning, policy optimization, genetic algorithm, training dataset optimization.

I. INTRODUCTION

REINFORCEMENT learning (RL) has demonstrated significant progress and achieved remarkable performance in diverse domains including robotics [1], [2], locomotion control [3], [4], strategy games [5], [6], manufacturing systems [7], and so on. RL algorithms have various choices of learning one or combinations of policies, action-value functions (Q-functions), value functions and/or environment models. In particular, actor-critic (AC) algorithms [8] are a class of RL algorithms that learn optimal policies. In a policy optimization process, an AC algorithm consists of approximate value function estimation, performance evaluation of the current policy, and policy update. Readers can refer to more principles and progresses of optimization methods in machine learning in a recent survey paper [9].

AC algorithms have been proved to be effective in solving complicated RL problems; see, e.g., [10], [11]. However, they always suffer from sampling inefficiency because of the fundamental restriction in using the on-policy learning approach. Roughly speaking, an on-policy approach requires new samples to be collected at every step of policy update. Such a sample collection manner causes a substantial increase in cost of experiments (for real-world scenarios) or computation (for simulated environments). It is worth mentioning that there have been notable works, e.g., [12]–[14], for improving the stability and sampling efficiency of AC algorithms in the on-policy framework. Trust region policy optimization (TRPO) [12] updates policies by taking the largest possible step, while satisfying a KL-divergence constraint on the closeness of old and new policies. A scalable trust region method [13] shows its improvement in sample efficiency. Proximal policy optimization (PPO) [14] replaces the hard KL constraint of TRPO with penalty on KL divergence and also proposes an alternate surrogate objective.

Alternatively, off-policy methods have also been extensively used with improved sampling efficiency. While an on-policy algorithm learns the value of the policy being carried out by the agent, including the exploration steps, an off-policy algorithm learns the value of the optimal policy independently of the agent's actions in executing a separate exploratory policy [15]. Typical off-policy algorithms include the well known Q learning (QL) [16] and related works such as deep Q-network (DQN) [17] and double-DQN [18]. An off-policy version of AC algorithm, Off-PAC, was proposed in [19]. In Off-PAC, the actor executes actions sampled from a fixed behavior policy and the critic learns an (off-policy) estimate of the value function for the current policy. The estimate is later used to update the weights of the critic and the policy. In [20], an off-policy integral RL algorithm based on AC networks was developed for optimal control of unknown systems subject to unknown disturbances with the aid of a disturbances compensation controller.

Off-policy algorithms also employ a technique called experience replay [21]. The concept of experience replay involves storing the agent's experience in a dataset. Then, mini-batches of samples from the experience dataset are drawn uniformly at random for a learning process. It logically separates the process of gaining experience and learning and has been proved to be effective in increasing sampling efficiency [22]. For instance, the concept was used in deep deterministic policy gradient (DDPG) [23] that concurrently learns a Q-function and a policy and uses the Q-function to update the policy. But DDPG is sensitive to hyper-parameters and may cause overestimation of the
learned Q-function. Then, a twin delayed DDPG (TD3) was proposed in [24] to address this overestimation issue. The concept of experience replay was also used in AC algorithms; see the AC with experience replay (ACER) algorithm introduced in [25]. It is worth mentioning that simple and convenient implementation of an off-policy adaptive QL method was developed in [26]. In particular, the experience replay technique is employed in the learning process in an AC neural network structure.

The methods for improving sampling efficiency of AC algorithms are not limited to those discussed above. For example, the soft actor-critic (SAC) algorithm introduced in [27] is another effective method that is based on the concept of entropy regularization. In SAC the policy is trained to maximize the trade-off between expected return and entropy. Research showed that sampling efficiency of SAC exceeds that of DDPG and other benchmarks by a substantial margin.

Other than the aforementioned on-policy and off-policy approaches, an offline or batch learning [28] approach has also gained researchers’ interest, where an experience buffer is maintained like off-policy RL but it is not updated actively from online interaction. It uses previously collected agent-environment interaction data to train policies [29]. Some recent research using this data driven paradigm for learning policies includes learning of navigation skills in mobile robots [30], learning of human preferences in dialogue [31], and learning of robotic manipulation [32], [33]. Readers can refer to a more detailed and holistic coverage of offline learning in a recent survey paper [34].

The proposed approach in this paper sits on the intersection of offline and off-policy learning approaches. Similar to offline learning, our approach learns from a static dataset, which is collected by running some prior policy but not continually updated (unlike off-policy algorithms). Also unlike most offline algorithms where a model-based RL setup is used, our work is completely model free, like off-policy methods. More specifically, the new approach is along with the research line of improving sampling efficiency of AC algorithms, especially using separated process of gaining experience and learning. We propose a strategy to optimize the experience dataset before it is used as a training dataset for learning an optimal policy. As a result, the training dataset requires significantly less samples collected from the AC process. Such a dataset optimization process is made of a best episode only operation, a policy parameter-fitness model, and a genetic algorithm (GA) module. The optimal policy network trained by the optimized training dataset exhibits superior performance compared with the conventional AC algorithm. Evaluation on standard benchmarks shows that the method improves sampling efficiency, ensures faster convergence to optimality and is more data-efficient than its counterparts. Since a GA module is used for optimizing the training dataset collected from an AC process, the algorithm in this paper is called a genetic algorithm aided actor-critic (GAAC).

It is worth noting that GA, as a class of evolutionary algorithms, has been successfully used as an alternative to RL [35], [36] or as an aid to improve performance of RL [37], [38]. For instance, in [37] evolution based learning is incorporated with RL’s gradient based optimization in a single framework to maintain a best policy population for evaluation and eventual convergence to an optimal policy. A collaborative evolutionary RL (CERL) was proposed in [38] which enables collective exploration of policies by policy gradient and neuroevolution modules to evolve an optimal policy network. GA was also used to optimize hyper-parameters of RL algorithms in [39] and evolve neural network weights [40], [41]. A GA based adaptive momentum estimation (ADAM) algorithm, called genetic-evolutionary ADAM (GADAM), learns better deep neural network models based on a number of unit models over generations [42].

The remaining sections of the paper are organized as follows. In Section II, we present the preliminaries and motivation of this paper. In Section III, we explain the proposed GAAC approach with optimized training datasets in details. In Section IV, we further discuss the GA module used in the dataset optimization process. Section V verifies the effectiveness of our approach in term of its comparison with other existing benchmarks. Finally, Section VI concludes the paper and discusses some related future research avenues.

II. PRELIMINARIES AND MOTIVATION

The paper is concerned about control of autonomous systems in a Markovian dynamical model represented by a conditional probability density function \( p(s_{t+1}|s_t, a_t) \) where \( s_t \in S \) and \( a_t \in A \) are the current state and control action respectively at time instant \( t = 1, 2, \ldots, \) and \( s_{t+1} \in S \) represents the next state at \( t + 1 \). Here, \( S \) and \( A \) represent the continuous state and action spaces, respectively. The objective is to learn a stochastic policy \( \pi(\tau|s_t) \) parameterized by \( \phi \). Now, the closed-loop trajectory distribution for the episode \( t = 1, \ldots, T \) can be represented by

\[
p_\phi(\tau) = p_\phi(s_1, a_1, s_2, a_2, \ldots, s_T, a_T, s_{T+1})
\]

\[
= p(s_1) \prod_{t=1}^{T} \pi_\phi(a_t|s_t)p(s_{t+1}|s_t, a_t)
\]

where \( \tau = (s_1, a_1, s_2, a_2, \ldots, s_T, a_T, s_{T+1}) \) represents the sequence of states and control actions. Denote \( r_t = R(a_t, s_{t+1}) \) as the reward generated at \( t \). The objective is to find an optimal policy, represented by the parameter

\[
\phi^* = \arg \max_\phi \mathbb{E}_{\tau \sim p_\phi(\tau)} \left[ \sum_{t=1}^{T} R(a_t, s_{t+1}) \right],
\]

which maximizes the objective function \( J(\phi) \).

We first revisit the conventional AC algorithm that is a class of model free RL algorithms for achieving the above optimal policy. Later, some improvements will be proposed in this paper. The AC Algorithm is a hybrid of a value based method and a direct policy optimization method [8]. A simplified diagram of the AC method is given in Fig. 1(a). The AC algorithm runs on two function approximators, the actor and the critic, generally modeled using neural networks (NNs).

The critic evaluates the current policy, as reflected by the updated state \( s_{t+1} \) and the reward \( r_t \) received after running the action \( a_t \) using the temporal difference (TD) learning. Let \( \psi_t \) represent the parameters (weights) of the critic NN that generates the value function \( V_{\psi_t}(s_t) \) whose target is the expectation of the
cumulative future rewards

\[
\sum_{k=0}^{\infty} \gamma^k r_{t+k} = r_t + \sum_{k=0}^{\infty} \gamma^k r_{t+1+k}
\]  

(1)
given \(s_t\). Here \(\gamma\) is the discount factor which determines the importance of rewards obtained from future states compared to that of the current state. As the target is unknown, the TD learner uses \(r_t + \gamma V_{\psi_t}(s_{t+1})\) as the target of \(V_{\psi_t}(s_t)\), noting the relationship (1). Therefore, one defines the TD error as

\[
\delta_t = r_t + \gamma V_{\psi_t}(s_{t+1}) - V_{\psi_t}(s_t).
\]  

(2)

Then, the simplest update of \(\psi_t\) can be

\[
V_{\psi_{t+1}}(s_t) \leftarrow V_{\psi_t}(s_t) + \alpha_c \delta_t,
\]  

(3)

by, e.g., using a gradient based approach, where \(\alpha_c\) is the learning rate.

The actor provides a probability distribution over all actions for each state, from where the action is sampled and run on the system. More specifically, let \(\phi_t\) represent the parameters (weights) of the actor NN that generates the policy parameters represented by the vector functions \(\mu_{\phi_t}(s_t), \sigma_{\phi_t}(s_t)\) for the given \(s_t\). Then, it gives the policy that follows the Gaussian distribution of mean \(\mu_{\phi_t}(s_t)\) and standard deviation \(\sigma_{\phi_t}(s_t)\), i.e., \(\pi_{\phi_t}(\alpha_t|s_t) = \mathcal{N}(\mu_{\phi_t}(s_t), \sigma_{\phi_t}(s_t))\). The action \(\alpha_t\) generates the aforementioned TD error \(\delta_t\) and hence an update approach for \(\phi_t\), e.g.,

\[
\phi_{t+1} \leftarrow \phi_t + \alpha_t \delta_t \nabla_{\phi_t} \log(\pi_{\phi_t}(s_t)) \tag{4}
\]

The idea is to minimize the loss that is the negative log likelihood of the Gaussian policy, with learning rate \(\alpha_t\).

For the convenience of presentation, we denote

\[
\theta_t = \begin{bmatrix} \mu_{\phi_t}(s_t) \\ \sigma_{\phi_t}(s_t) \end{bmatrix}.
\]

From above, the AC algorithm recursively updates the policy parameters using the observations \(d_t = \{s_t, \theta_t, \delta_t\}, t = 1, \ldots, T\), in the scenario that the system is fully observed. In particular, it is expected that, with a (very) large \(T\), the optimal policy can be found as \(\phi_T \rightarrow \phi^*\). A more effective way is to keep each episode reasonably small according to the real scenario (e.g., an episode is naturally finished when a certain task is achieved) and repeat multiple episodes. More specifically, we collect the data \(d^e_t, t = 1, \ldots, T, e = 1, \ldots, E\), in the sequence of

\[
d^1_t, d^2_t, \ldots, d^E_t, \ldots, d^{E_1}_t, d^{E_2}_t, \ldots, d^{E_T}_t
\]

where the superscript \(e\) represents the episode index. It is noted that the episode length \(T_e\) for each episode is not necessarily the same. Then, it is expected that, with a (very) large \(E\), the optimal policy can be found as \(\phi^{E}_T \rightarrow \phi^*\).

From above, a successful AC algorithm usually requires a large amount of costly experimental samples. It motivates the proposed approach that relies on considerably lesser experimental samples that can be optimized and form a training dataset for an optimal policy network. The optimization of training datasets is conducted using the multiple ideas listed below. They will be elaborated in the following section. As a result, the new algorithm improves the conventional AC algorithm through utilizing the samples more efficiently and achieving faster convergence to the optimal policy. The primary contributions and novelties of this paper are listed below.

1) Best episode only (BEO): The conventional AC algorithm is conducted on real experiments for multiple episodes and a raw training dataset is collected. Only the best episodes (selected from repeated rounds) in terms of the associated cumulative rewards will be retained to make the final training dataset.

2) Parameter fitness model (PFM): A PFM NN is created to update the samples more efficiently and achieving faster convergence to the optimal policy. The primary contributions and novelties of this paper are listed below.

3) Dataset optimization: A certain amount of policy parameter vectors in the training data are updated through comparison with other candidates in their neighborhoods in terms of the TD errors evaluated by the PFM. The selection of candidates typically follows a GA module.
et al. (6)

\[ D = \{ (e_1, \theta^e_1), (e_2, \theta^e_2), \ldots, (e_M, \theta^e_M) \} \]

... episodes per round, i.e., \( \rho = \max \{ \epsilon | t = 1, \ldots, T_e \} \), \( e \in \mathcal{E} \}

Then, the dataset from the best episodes, i.e.,

\[ D_1 = \{ d_t^e \mid t = 1, \ldots, T_e, e \in \mathcal{E} \} \]

will be used to train the so-called parameter-fitness model in stage 2. Similarly, we define

\[ W_1 = \{ \{ s^e_t, \theta^e_t \} \mid t = 1, \ldots, T_e, e \in \mathcal{E} \}. \]

We refer the strategy of selecting the best rewarding episode per round as the BEO approach. There are two factors which play crucial role in efficient learning of a policy from past (collected) experience, i.e., sample balance and data diversity. In a typical training dataset (or replay buffer) the quantity of samples with poor rewards easily outnumbers the quantity of samples with high rewards leading to sample imbalance, which results in slow policy learning and decreased sample efficiency. Again training a policy while considering only the best experience or high reward samples, does not effectively leverage from the policy’s exploration behavior. As a result, such a training dataset may suffer from poor data diversity and cause the policy to over-fit and perform myopically.

The proposed BEO strategy counters with these two related issues. In particular, through the BEO approach we retain one “best in the round” episode, over multiple (\( M = 10 \)), short (\( N \leq 6 \)), and mutually uncorrelated rounds of AC policy learning. It is worth noting that there is no fixed threshold for “best” episode selection, rather “best” episode selection is from the perspective of each uncorrelated short rounds. This facilitates selection of even relatively poor rewarding episodes for being the best in a certain round. So ultimately the policy learns from a training dataset, consisting of data from a selection of episodes, with reduced sample imbalance. This enables the algorithms to learn high rewarding policies faster. Additionally, these short rounds are mutually uncorrelated and are fresh instances of AC policy learning (networks reset at onset of each round), which improves exploration behavior leading to enhanced data diversity in the collected dataset \( D_1(\mathcal{W}_1) \).

III. AC POLICY WITH OPTIMIZED TRAINING DATASETS

The new AC policy with optimized training datasets is a three stage process. In each stage, we will explicitly explain how the raw training datasets are collected from experiments and how they are optimized, represented by the sequence of

\[ W_o \rightarrow W_1 \rightarrow W_2 \]
as elaborated below. The schematic diagram of the three stages is illustrated in Fig. 1.

A. Stage 1: Data Collection and Selection of Best Episode

The first stage starts with collecting data from running the convention AC algorithm for totally \( E \) episodes that are grouped in \( M \) rounds of \( N \) episodes per round, i.e., \( E = MN \). The data collection stage’s setup of \( M \) repeated rounds of \( N \) episodes is illustrated in Fig. 2. The raw dataset collected from the experiments is denoted as

\[ D_o = \{ d_t^e \mid t = 1, \ldots, T_e, e = 1, \ldots, E \}. \]

Correspondingly, the following input-output pairs

\[ W_o = \{ \{ s^e_t, \theta^e_t \} \mid t = 1, \ldots, T_e, e = 1, \ldots, E \}. \]

are for the actor NN. In other words, the training dataset for the actor NN is \( W_o \).

Next, for each episode, we define the total reward as \( r^e = \sum_{t=1}^{T_e} r_t^e \), based on which we can select the best episode of each round, that is,

\[ e_m = \arg \max_{m=1, \ldots, M} \sum_{t=1}^{T_e} r_t^e \]

As a result, \( \mathcal{E} = \{ e_1, \ldots, e_M \} \) is called the set of best episodes. It is worth mentioning that, for each round, both the actor and critic networks are reinitialized and they start learning from scratch and the learning continues for \( N \) episodes.
predicted value of the NN under training. The PFM is further improved by running repeated cross validation tests.

Next, we randomly pick a subset \( D' \subset D_1 \) of typically \( \eta(\%) \) population and optimize every tuple \( d_i^t \) in \( D' \) as follows. Define a neighborhood of \( \theta^c_i \) as \( B(\theta^c_i) \) and find the optimal \( \theta \) within this neighborhood in the sense of

\[
\bar{\theta}^c_i = \arg \max_{\theta \in B(\theta^c_i)} \rho(s^c_i, \theta), \forall d_i^t \in D'.
\]

(9)

Here, \( \eta \) is a hyperparameter and the appropriate value is determined through hyperparameter search, with more analysis in Section V-B3.

Specifically, optimization of (9) is pursued by a GA module which is explained in details in the next section. This optimization step is crucial since the AC+ BEO based exploratory data in \( D_1(W_1) \) is quantitatively small and collected from multiple uncorrelated instances (or rounds) of AC policies in their very early learning process. And so if this data is directly used for training, then it may result in poor performance of the final policy; see the ablation studies and discussion in Sections V-A3 and V-B2. We thus use GA and a surrogate PFM to optimize and update \( \eta \) of \( W_1 \) before training the optimal policy network. For a given state \( s^c_i \), the corresponding policy parameter is optimized as \( \bar{\theta}^c_i \) that gives a larger TD error, calculated by the PFM, due to

\[
\rho(s^c_i, \bar{\theta}^c_i) > \rho(s^c_i, \theta^c_i) = \delta^c_i.
\]

For complement of notation, we define

\[
\bar{\theta}^c_i = \theta^c_i, \forall d_i^t \in D_1 \setminus D'.
\]

(10)

That is, the policy parameters in the subset \( D_1 \setminus D' \) are untouched. Now, it is ready to have the optimized dataset

\[
W_2 = \{ \{ s^c_i, \bar{\theta}^c_i \} \mid t = 1, \ldots, T_e, e \in E \}
\]

(11)

that will be used in Stage 3.

C. Stage 3: Optimal Policy Training

In the final stage, an optimal policy NN is trained using the dataset \( W_2 \). Since a continuous state stochastic policy is concerned, the actions that are sampled from the policy come from a probability distribution given the state. Similar to the mixture density network concept as introduced in [43], the optimal policy NN predicts a mean \( \mu \) and a standard deviation value \( \sigma \), which define a Gaussian distribution. In particular, it is of the same structure as the actor NN whose trained parameters are represented by \( \phi^* \) satisfying

\[
\bar{\theta}^c_i = \begin{bmatrix} \mu_{\phi^*}(s^c_i) \\ \sigma_{\phi^*}(s^c_i) \end{bmatrix}, \forall \{ s^c_i, \bar{\theta}^c_i \} \in W_2.
\]

The final optimal policy is \( \pi_{\phi^*}(a_t|s_t) = \mathcal{N}(\mu_{\phi^*}(s_t), \sigma_{\phi^*}(s_t)) \). When implemented, for any given state, the trained optimal policy NN is able to give a set of policy parameter that implies an action distribution and an action sample. A more specific expression of the Gaussian distribution is as follows

\[
\pi_{\phi^*}(a_t|s_t) = \frac{1}{\sqrt{2\pi\sigma^2_{\phi^*}(s_t)}} \exp \left[ -\frac{(a_t - \mu_{\phi^*}(s_t))^2}{2\sigma^2_{\phi^*}(s_t)} \right],
\]

which is graphically illustrated in Fig. 3.
B. Initial Population

Given a state \( s_t^* \), the GA process starts its evolution for the optimal policy parameters from a batch of candidate optimal parameters \( G^{(0)} = \{\theta_i^{(0)}, \ldots, \theta_j^{(0)}\} \) (called the initial population) generated in the neighborhood \( \mathcal{B}(\theta^*_t) \), i.e., \( G^{(0)} \subseteq \mathcal{B}(\theta^*_t) \). The initial population size of \( G^{(0)} \) is denoted as \( J \). The neighborhood of a parameter \( \theta^*_t \) is defined as \( \mathcal{B}(\theta^*_t) = [\theta_{\min}, \theta_{\max}] \) where \( \theta_{\min} \) and \( \theta_{\max} \) are the minimum and maximum values of all the \( \theta^*_t \) collected in \( D_1(\mathcal{V}_1) \), respectively.

To encourage exploration, the initial population \( G^{(0)} \) is generated as a combination of two separately obtained but equal sized sub populations, i.e., \( G^{(0)} = G^{(0)}_1 \cup G^{(0)}_2 \). In particular, the subset \( G^{(0)}_1 = \{\theta_1^{(0)}, \ldots, \theta_{j/2}^{(0)}\} \) contains the parameters \( \theta_j^{(0)} \) randomly selected from a set of discrete values \( \{\theta_{\min}, \theta_{\min} + \epsilon, \theta_{\min} + 2\epsilon, \ldots, \theta_{\max}\} \) where \( \epsilon = (\theta_{\max} - \theta_{\min})/\ell \) for some integer \( \ell > 1 \) is used to characterize the resolution of the selected parameters. The value of \( \epsilon \) is close to 0.05 in the experiments of this paper. The other subset \( G^{(0)}_2 = \{\theta_{j/2+1}^{(0)}, \ldots, \theta_j^{(0)}\} \) contains the parameters sampled from the distribution \( N(\theta^*_t, 0.1) \) and truncated to fit into \( \mathcal{B}(\theta^*_t) \).

The optimization process uses the PFM to generate the fitness values for this batch of candidate population, i.e., \( \rho(s_t^*, \theta) \), \( \forall \theta \in G^{(0)} \), so that the optimal policy parameter from the initial population can be selected.

C. Selection of Parents

GA learns/evolves the optimal parameters from the initial population. We represent the generation as \( G^{(u)} \) with the candidate parameter population given as \( G^{(u)} = \{\theta_1^{(u)}, \ldots, \theta_J^{(u)}\} \), where \( u \geq 0 \) is the number of generations. The corresponding fitness value predicted by the PFM is given by \( \delta_i^{(u)} = \rho(s_i^*, \theta_i^{(u)}) \), \( i = 1, \ldots, J \). Then, the selection probability of the unit parameter vector \( \theta_i^{(u)} \) as a candidate parent is defined using the following Softmax equation

\[
p_i = \frac{\exp(\delta_i^{(u)})}{\sum_{j=1}^J \exp(\delta_j^{(u)})}.
\]

Let \( L \) be the number of parent-pairs and pick \( G_{1}^{(u)} = \{\theta_i^{(u)}, \ldots, \theta_L^{(u)}\} \) as a subset of \( G^{(u)} \) and \( G_{2}^{(u)} = G^{(u)} \setminus G_{1}^{(u)} \) such that \( p_i \geq p_j \) for all \( \theta_i^{(u)} \in G_{1}^{(u)} \) and \( \theta_j^{(u)} \in G_{2}^{(u)} \). In other words, \( G_{1}^{(u)} \) consists of the \( L \) parameter vectors of the highest selection probability. Next, we randomly re-order the sequence \( i_1, \ldots, i_L \) as \( j_1, \ldots, j_L \) such that \( i_q \neq j_q \), \( q = 1, \ldots, L \). Then, the set of parent pairs is defined as \( \mathcal{P} = \{(\theta_{i_1}^{(u)}, \theta_{j_1}^{(u)}), \ldots, (\theta_{i_L}^{(u)}, \theta_{j_L}^{(u)})\} \).

D. Crossover

In GA, the off-springs inherit genes (vector elements) from parents in the crossover process, which propagates the better traits of parents to their children. The child parameter vector thus generated by the crossover process can be represented as \( \hat{\theta}_{q}^{(u)} \) from the pair \( (\theta_{i_q}^{(u)}, \theta_{j_q}^{(u)}) \) in \( \mathcal{P} \) for \( q = 1, \ldots, L \). Let \( h \) be the \( h \)-th element of a vector. More specifically, the crossover process is represented by

\[
\hat{\theta}_{q}^{(u)}[h] = \begin{cases} 
\text{bool(rand} \leq p_{i_q,j_q})\theta_{i_q}^{(u)}[h] 
+ \text{bool(rand} > p_{i_q,j_q})\theta_{j_q}^{(u)}[h] 
\end{cases}
\]

Here, bool represents a binary function that returns 1 if the condition is satisfied and 0 otherwise, rand denotes a random number in [0,1], and \( p_{i_q,j_q} = p_i/(p_i + p_j) \) is the relative probability. Obviously, the larger \( p_i \) relative to \( p_j \), the higher chance that the element parameter from the parent \( \theta_{i_q}^{(u)} \) is inducted into the child \( \hat{\theta}_{q}^{(u)} \). After the crossover process, the children population is generated as \( \hat{G}^{(u)} = \{\hat{\theta}_1^{(u)}, \ldots, \hat{\theta}_L^{(u)}\} \).

E. Mutation

To avoid trapping in local optima, GA uses a mutation operation. In this process we introduce randomness into the child parameter vector to encourage exploration. For each child parameter vector \( \hat{\theta}_q^{(u)} \), \( q = 1, \ldots, L \), the element parameter is mutated according to the following equation:

\[
\hat{\theta}_q^{(u)}[h] = \begin{cases} 
\text{bool(rand} \leq \tilde{p}_q)\theta_{i_q}^{(u)}[h] 
+ \text{bool(rand} > \tilde{p}_q)\theta_{j_q}^{(u)}[h] 
\end{cases}
\]

where \( \tilde{p}_q = \alpha_m(1-p_{i_q} - p_{j_q}) \) is the mutation rate (the constant \( \alpha_m \) is the base mutation rate). Therefore, the child parameter vectors with good parents of higher selection probabilities have lower mutation rates. After the mutation process, the children population is generated as \( \hat{G}^{(u)} = \{\hat{\theta}_1^{(u)}, \ldots, \hat{\theta}_L^{(u)}\} \).

F. Evolution and Stop

Now, the next generation becomes \( G^{(u+1)} = \hat{G}^{(u)} \cup G^{(u)} \) where the \( L \) elements in \( \hat{G}^{(u)} \) are from the offspring generation through crossover and mutation and the \( J - L \) elements in \( G^{(u)} \) are the leftover individuals. The evolutionary process stops if there is no significant improvement of fitness between consecutive generations. Considering two consecutive generations \( G^{(u)} \) and \( G^{(u+1)} \), the stopping criterion is

\[
|\Sigma_{i=1}^J \delta_i^{(u+1)} - \Sigma_{i=1}^J \delta_i^{(u)}| \leq \alpha_s
\]

where \( \alpha_s \) is a small positive constant called the evolution stop threshold.

V. EXPERIMENTAL EVALUATION

Experimental results are reported in this section to compare the efficiency of the proposed GAAC algorithm with the conventional AC algorithm. The experiments were conducted on Mountain Car Continuous (MCC)-v0 and Swimmer-v3 [44], two benchmarks from OpenAI Gym, which are elaborated in the following two subsections, respectively.

A. Mountain Car Continuous-V0

The MCC environment consists of an underactuated car that starts its journey from the valley region between two hills. As to reach the flag present on top of the right hill, it must drive
back and forth through the slope of the left and right hills to gain enough momentum to reach the goal. When the absolute value of the action that is applied to the car is larger, the reward is smaller (more negative). MCC is a sparsely rewarded environment where it only occasionally provides useful reward for the algorithm to leverage on. Here the reward remains always negative unless the car makes it to the flag. In that case the car receives a +100 reward. More specifically, the state is \( s_t = [x_t, y_t] \), with \( x_t \) being the car position and \( y_t \) the speed, the action \( a_t \) is the car acceleration (force), and \( x_G = 0.45 \) the target position (i.e., position of the flag). The reward function is defined as

\[
R(a_t, s_{t+1}) = \begin{cases} 
-0.1a_t^2, & x_{t+1} \neq x_G \\
+100, & x_{t+1} = x_G 
\end{cases}
\]

The action value is continuous within the range \([-1.0, 1.0]\), out of which the value is clipped to its maximum or minimum value. For every episode, the initial position \( x_1 \) is set to a random value within the range \([-0.6, -0.4]\) and the initial speed \( y_1 = 0 \), and the episode runs and resets after running for 1,000 steps. The episode may finish prematurely if the car reaches its goal sooner, i.e., once \( x_{t+1} = x_G \) is achieved.

The NN structures used in the experiments are same for all the algorithms and the parameters for AC and GAAC are summarized in Table I.

### 1) Successful and Failed Episodes Using AC: The AC algorithm starts with a policy of random initial parameters. It may reach the target and win a reward of +100 in an episode (called a successful episode) or get “stuck at local minima” (called a failed episode) and sometimes the policy cannot recover from such episodes leading to a failed policy (marked in red), see Fig. 4(b). If the AC algorithm attains a successful episode in the first few trials then with every episode the policy is expected to gradually improve the cumulative result with increasing rewards. It was observed that in about 200 episodes a cumulative reward average of 92.8 was obtained and it was increased to 94.2 in 5,000 episodes. Fig. 4(a) shows the trajectories of the car for the 200 episode trained AC policy. The car was able to reach the goal position at \( x_G = 0.45 \) but the final speeds were relatively large. The performance of the AC is plotted in Fig. 4(b) for the first 200 episodes. The cumulative reward of an episode falls short of 95. Both successful and failed episodes can be observed in the figure.

### 2) Optimization of Training Datasets: The critical mechanism of the proposed GAAC approach is optimization of training datasets. We first conducted the AC algorithm for 10 runs with \( N = 3 \) episodes each. And we chose the best episode of the round which gives the highest cumulative reward. At the onset of each round we reset the networks and run the AC policy from scratch. Out of the ten best episodes, there was one good episode in which the target was achieved and the other nine were bad. In the ten episodes, we collected totally \( |D_1| = 9,654 \) samples where the operator \(|\cdot|\) represents the cardinality of a set. It is noted that a failed episode typically has more samples than a good one as the latter may stop earlier once the target is reached. In average, each episode contributes 965 samples. Next, the GA module optimized \( \eta = 25\% \) of the total samples, i.e., \( |D'| = 2,416 \). Then, the optimized dataset was used for training the optimal policy network. Another 80 episodes were
TABLE II
EVALUATION OF OPTIMAL POLICY UNDER DIFFERENT SUCCESSFUL AND FAILED TRAINING EPISODE MIXTURE RATIOS IN MCC

| episode mixture ratio | $|D_1|$: samples by BEO | $|D_1'|$: GA optimized samples | failed testing episodes | Cumulative Reward range |
|-----------------------|--------------------------|-------------------------------|------------------------|------------------------|
| 1.9                   | 9,654                    | 2,416                         | 1 out of 80           | 92 - 93               |
| 2.8                   | 8,894                    | 2,224                         | 0 out of 80           | 95 - 98               |

tested on the trained policy and only one episode failed. The cumulative rewards were located in the range between 92 and 93 for the good episodes. The results are summarized in Table II. The same process was repeated and out of the ten best episodes there were two good episodes and eight bad ones. Their results are also recorded in the same table for comparison. With more good samples, all of the 80 testing episodes were successful and the cumulative rewards were improved to the range between 95 and 98. It is worth mentioning that the successful/failed episode ratio is 1:9 or 2:8 in the experiments summarized in Table II because successful policies are rare in MCC in the early stage of the AC algorithm for the local minima issue. The case with 2:8 is used in the subsequent discussion.

3) Ablation Studies: The effectiveness of the design is evaluated through ablation studies of four algorithms. The first one is the conventional AC algorithm where the dataset collected from the actor NN is $W_1'$ from which the optimal policy is directly trained. The second one is a partial algorithm of GAAC, called AC+GA, where the AC explored data $W_1'$ is directly used for GA optimization and training of the optimal policy network in stage 2 and stage 3, respectively, that is, the BEO component in stage 1 is excluded. The third one is another partial algorithm including stage 1 and stage 3, but not stage 2, called AC+BEO. In other words, the dataset $W_1'$ from stage 1 is directly used in stage 3 for training the optimal policy network. The fourth one is the full three-stage AC algorithm with both BEO and GA module, i.e., GAAC, where the dataset $W_2'$ is used for training the optimal policy network.

Performance comparison among the four algorithms is demonstrated in Fig. 5. The result from the AC algorithm has been explained in Fig. 4. In the AC+GA algorithm, due to the absence of the BEO module, all the 30 training episodes were from a single continually learning AC policy (i.e., one round). As mentioned before, successful policies are rare in MCC in the early stage of the AC algorithm, so a failed policy is more likely and recorded here. The GA refined samples from these training episodes were not effective for learning an optimal policy. The AC+ BEO algorithm learnt the policy using the samples collected from only 30 episodes even though the cumulative reward in the range between 92 and 93 did not significantly outperform the AC algorithm. It is worth mentioning that these 30 episodes were from ten rounds in the BEO stage. The BEO mechanism for using a small percentage (two out of ten) of successful policies demonstrated its effectiveness of resolving the aforementioned local minima issue.

Finally, the complete GAAC algorithm was implemented using the same 30 episodes as in AC+BEO. In Fig. 5(a), the GAAC trajectory shows that the car was able to reach the goal position with a lower speed. The result in Fig. 5(b) shows that the GAAC algorithm performs better than AC, AC+GA and AC+BEO. It achieved an average cumulative reward of 95.83 over 80 testing episodes, again using the samples collected from only 30 episodes. For the conventional AC algorithm, it took more than 5,000 episodes to attain the same level of optimality in terms of the average cumulative reward.

4) Comparison With Other Benchmarks: To further evaluate the performance of GAAC, we tested it against some of the latest benchmarks, e.g., SAC [27], TD3 [24], TRPO [12] and PPO [14]. We used a baseline library called stable-baselines [45] for generating the data for the benchmarks. For each algorithm, we used the data from five repeated tests of the policy. The experimental results from the algorithms are plotted in Fig. 6 that shows a solid mean line surrounded by a lightly shaded area representing its variance in the five repeated tests. The training episodes for the five repeated tests are represented by one dot as the average reward for clarity. For the GAAC algorithm, only the mean of the training data is shown for the first 30 episodes for neat presentation. The benchmarks use default hyperparameters of the stable-baselines library. They also use a multilayered policy network similar to GAAC.
Fig. 6. Performance comparison of the GAAC algorithm with the existing benchmarks in MCC experiments.

**TABLE III**

| Algorithm | MCC-v0    | Swimmer-v3 |
|-----------|-----------|------------|
| SAC       | $86.243 \pm 27.759$ | $21.879 \pm 16.333$ |
| TD3       | $26.245 \pm 54.071$ | $24.495 \pm 23.065$ |
| TRPO      | $66.486 \pm 38.092$ | $26.380 \pm 8.961$ |
| PPO       | $-5.592 \pm 5.309$  | $32.182 \pm 3.621$ |
| AC        | $90.440 \pm 25.434$ | $7.189 \pm 13.887$ |
| GAAC      | $95.684 \pm 1.146$  | $78.560 \pm 29.914$ |

All of the benchmark algorithms frequently suffer from the local minima issue in MCC as discussed before. For the purpose of comparison, we only selected the successful policies in Fig. 6 except the PPO algorithm that failed to learn a successful policy. The plots show that GAAC attained a higher level of optimality and faster convergence to the optima by consuming the data from only 30 episodes. So, GAAC learned an optimal policy with significantly less data samples from the environment than the existing benchmarks in this comparison.

The 31st-100th episodes in Fig. 6 are called the evaluation episodes. So, there are 350 evaluation episodes recorded in figure from the five repeated tests. The quantitative comparison is also summarized in Table III in terms of the mean and standard variation of the rewards for these 350 evaluation episodes. It concludes that GAAC outperforms the benchmarks by achieving the highest reward of $95.684 \pm 1.146$.

**B. Swimmer-v3**

Swimmer-v3 represents a planar robot swimming in a viscous fluid. It is made up of three links (head, body and tail) and two actuated joints connecting them. The system dynamics can be described in a ten-dimensional state space, which consists of position and velocity of the center of body (4), angle and angular velocity of center of body (2), and angle and angular velocity of the two joints (4). The two-dimensional action space consists of the torques applied on the two actuated joints.

The objective in this experiment is to stimulate the maximal forward (the positive x-axis) moving/swimming by actuating the two joints, with the reward function defined as follows

$$R(a_t, s_{t+1}) = v_x^{t+1} - 0.0001 \|a_t\|_2^2$$

where $v_x$ (an element of $s$) is the forward velocity and $a_t$ the two-dimensional action torques. The value of an action torque is continuous within the range $[-1.0, 1.0]$, out of which the value is clipped to its maximum or minimum value. For every 1,000 steps, called an episode, the environment is reset and the swimmer starts at a new random initial state. There is no premature termination condition applied to an episode.

1) **Optimization of Training Dataset:** We conducted the AC policy for $M = 10$ rounds with $N = 6$ episodes per round. Choosing the best episode in each round we collected $|D_1| = 10,000$ samples. Each episode here contributes equally 1,000 samples. Next the GA module optimizes $\eta = 15\%$ of total samples, i.e., $|D'| = 1,500$. The design parameters for AC and GAAC in the Swimmer environment are also summarized in Table I.

2) **Ablation Studies:** In Fig. 7(a), we compare the motion trajectories of the swimmer’s center of body in the x-y plane, using the four mentioned algorithms, i.e., AC, AC+BEO, AC+GA and GAAC. It is observed that the swimmer performed better...
many samples may also cause loss of diversity resulting in poor performance.

4) **Comparison With Other Benchmarks:** The comparison of GAAC with other benchmark algorithms is presented in Fig. 9. The plots show that the GAAC algorithm produced substantially better performing policies in this high dimension environment, with very few (60) learning episodes. Indeed, GAAC, trained with 60 episode, outperformed the benchmark algorithms even after they have been trained for more than 500 episodes, i.e., 50,000 steps (not shown in the figure). The outstanding performance of GAAC is also demonstrated by the quantitative comparison summarized in Table III for the 200 evaluation episodes, i.e., the 61st-100th episodes repeated five times.

VI. **CONCLUSION AND FUTURE WORK**

In this paper, we have proposed an optimal AC policy with a GA optimized training dataset. The process is made of a best episode only operation, a policy parameter-fitness model, and a genetic algorithm module. The new approach, called GAAC, can learn an optimal policy with significantly less number of samples as compared to the latest benchmarks, thus demonstrating the improvement in sampling efficiency and convergence speed over the conventional AC algorithm. In this work, GAAC is evaluated on two dynamic control environments with different state and action dimensions and its superiority is exhibited. It is an interesting future work to apply the proposed algorithm in different types of control tasks in more challenging environments. Moreover, the idea of optimizing training dataset can be integrated with other advanced RL algorithms like SAC, TD3, etc. Improvement with hyper-parameter tuning techniques for the neural networks and deep neural networks will be other interesting topics for future research.

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