Multi-Batch Experience Replay for Fast Convergence of Continuous Action Control

Seungyul Han and Youngchul Sung†

Abstract

Policy gradient methods for direct policy optimization are widely considered to obtain optimal policies in continuous Markov decision process (MDP) environments. However, policy gradient methods require exponentially many samples as the dimension of the action space increases. Thus, off-policy learning with experience replay is proposed to enable the agent to learn by using samples of other policies. Generally, large replay memories are preferred to minimize the sample correlation but large replay memories can yield large bias or variance in importance-sampling-based off-policy learning. In this paper, we propose a multi-batch experience replay scheme suitable for off-policy actor-critic-style policy gradient methods such as the proximal policy optimization (PPO) algorithm [1], which maintains the advantages of experience replay and accelerates learning without causing large bias. To demonstrate the superiority of the proposed method, we apply the proposed experience replay scheme to the PPO algorithm and various continuous control tasks. Numerical results show that our algorithm converges faster and closer to the global optimum than other policy gradient methods.

I. INTRODUCTION

Reinforcement learning aims to find an optimal policy that maximizes the cumulative reward in an MDP environment. There exist several well-known reinforcement learning algorithms to yield high performance in MDP environments with discrete state and action spaces such as SARSA and Q-learning, which obtain optimal policies by solving the iterative Bellman equation [2]–[4]. These methods store the Q-values of all state-action pairs to solve the Bellman equation. However, it is difficult to store all Q-values when the state dimension is too large or the action has continuous values. In order to learn in large state-space environments, function approximation can be applied [5]. For example, deep-Q-learning (DQN) [6] approximates the Q-value by using a neural network to generalize the Q-values from limited visited states to all states and outperforms the human level in Atari games which have large state dimensions and discrete action spaces [7]. However, DQN handles only finite actions due to its finite Q-network outputs and has difficulty in controlling tasks with continuous action spaces. To deal with such continuous control tasks, policy gradient methods were proposed, in which the policy is parameterized and is directly optimized based on an objective function [8].

Recent policy gradient methods in deep reinforcement learning use a policy neural network to optimize the objective function given by the expected discounted cumulative reward and the policy gradient is given by the policy gradient theorem, which states that the policy gradient is the expectation of the product of the score function and the advantage function [8]. However, the true expectation required for policy update cannot be computed exactly since we do not know the true underlying distribution and cannot visit all states and actions. Hence, an empirical estimate based on samples is used instead of the true expectation and the policy parameters are updated based on stochastic gradient descent [4]. Here, stochastic gradient descent for objective maximization is too slow to converge and is unstable since it can go even to the reverse direction of the true gradient. To resolve such difficulties and improve performance over the simple stochastic gradient descent, several algorithms were proposed for policy gradient methods. For example, natural gradient descent for policy optimization exploiting the Fisher information matrix in the policy parameter space was proposed to find the gradient direction in the constrained parameter space [9], [10], and the trust region policy optimization (TRPO) algorithm [11] was proposed to generalize the natural gradient method to any policies within a Kullback-Leibler (KL) divergence constraint to guarantee monotone...
improvement of the objective function. However, the large importance sampling weights in TRPO can yield large variances and hence PPO [11] considers clipping of the importance sampling weights and improves the performance in most action control tasks compared to the previous policy-gradient-based methods. However, we observe that PPO still has poor performance than TRPO in some tasks and there exists a room for improvement by using some experience replay technique. Experience replay techniques were previously used in DQN [6] and actor-critic with experience replay (ACER) [12] to explore states and actions from the previous policies and to stabilize optimization by reducing the correlation among samples for stochastic gradient descent. In these previous methods, the authors considered experience replay in which replay samples are generated from many previous policies, but we observe that such experience replay yields large importance sampling weights between samples of old policies and the newest sample and that clipping of the large importance sampling weights yields large biases, as described in [12]. Therefore, in this paper, we propose an experience replay scheme suitable to off-policy actor-critic-style policy gradient methods such as PPO to take advantage of experience replay but to reduce the distance among the policies in experience replay based on a few multiple batches of reply samples. We apply our experience replay scheme to PPO and show that our algorithm significantly outperforms both PPO and TRPO in terms of fast convergence and global convergence on various continuous control tasks.

Notations: \( X \sim P \) means that the random variable \( X \) follows the probability distribution \( P \). \( \mathcal{N}(\mu, \sigma^2) \) denotes the Gaussian distribution with mean \( \mu \) and variance \( \sigma^2 \). \( \mathbb{E}[\cdot] \) denotes the expectation operator. \( D_{KL}(P||Q) \) denotes the Kullback-Leibler divergence between the probability distributions \( P \) and \( Q \).

II. BACKGROUND

A. Markov Decision Processes and Policy Gradient Methods

We first provide an overview of MDPs and policy gradient methods in reinforcement learning. An MDP is defined as \( \langle S, A, \gamma, P, r \rangle \), where \( S \) denotes the state space, \( A \) denotes the action space, \( \gamma \) is the discount factor, \( P \) is the state transition probability, and \( r \) is the reward function. At time step \( t \), the agent takes the action \( a_t \in A \) to the environment in state \( s_t \in S \). Then, the environment returns the reward \( r(s_t, a_t) \) to the agent and the state changes in a Markovian manner, i.e., the next state \( s_{t+1} \sim P(s_{t+1}|s_t, a_t) \). In reinforcement learning, the agent wants to choose the action \( a_t \) for the given state \( s_t \), i.e., to design the stochastic policy \( \pi(a_t|s_t) \) for maximizing the discounted total reward sum \( J = \mathbb{E}_{s_t \sim P, a_t \sim \pi(|s_t)} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right] \). To obtain an optimal policy, a policy gradient method parameterizes \( \pi \) as \( \pi_\theta \), and updates the policy parameter \( \theta \) to the gradient direction of the discounted total reward sum, \( \nabla_\theta J(\theta) \), derived as [8]

\[
\nabla_\theta J(\theta) = \mathbb{E}_{s_t \sim \rho_{\pi_\theta}, a_t \sim \pi_\theta(|s_t)} [\nabla_\theta \log \pi_\theta(a_t|s_t) Q_{\pi_\theta}(s_t, a_t)],
\]

where \( \rho_{\pi_\theta}(s) = \sum_{t=0}^{\infty} \gamma^t P(s_t = s|s_0; \pi_\theta) \) is the unnormalized stationary distribution of states and \( Q_{\pi_\theta}(s_t, a_t) = \mathbb{E}_{s_{t+1} \sim P, a_{t+1} \sim \pi_\theta(|s_{t+1})} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right] \) is the state-action value function. With the state value function defined as \( V_{\pi_\theta}(s_t) = \mathbb{E}_{s_{t+1} \sim P, a_{t+1} \sim \pi_\theta(|s_{t+1})} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right] \), which is the mean of the state-action value function averaged over the actions, we can replace \( Q_{\pi_\theta}(s_t, a_t) \) in [8] with the advantage function \( A_{\pi_\theta}(s_t, a_t) = Q_{\pi_\theta}(s_t, a_t) - V_{\pi_\theta}(s_t) \) since subtracting the state value function from \( Q_{\pi_\theta}(s_t, a_t) \) does not affect the expectation value in [8] [13]. It is known that using the advantage function instead of the state-action value function in the policy gradient formula [11] reduces the variance since the quantity in [8] is centered around the mean without affecting the expectation value by using the advantage function.

B. Minorization and Maximization: The Surrogate Function with a KL Constraint

A policy gradient method based on simple stochastic gradient based on [11] does not show good performance. To improve the performance and guarantee monotone performance improvement, the minorization and maximization (MM) technique [14] was applied for policy gradient [11]. For this, as in typical MM methods, the objective function relationship between the old policy \( \pi_\theta \) and the updated policy \( \pi_{\tilde{\theta}} \) is derived as [11], [15]

\[
J(\tilde{\theta}) = J(\theta) + \mathbb{E}_{s_t \sim \rho_{\pi_\theta}, a_t \sim \pi_{\tilde{\theta}}[A_{\pi_{\tilde{\theta}}}(s_t, a_t)],
\]

where \( \rho_{\pi_{\tilde{\theta}}} \) is the unnormalized stationary distribution of states following the updated policy \( \pi_{\tilde{\theta}} \). Note that the policy should be optimized over the variable \( \tilde{\theta} \) to be updated not over the old parameter \( \theta \). However, it is difficult to
evaluate $\rho_{\pi_\theta}$ (even empirically) for computation of $J(\tilde{\theta})$ since it is the unnormalized stationary distribution of states following the updated policy and the policy is not updated yet at the time of update. Thus, it is suggested to use a surrogate function for $J(\tilde{\theta})$, given by \[ 11 \]

$$J(\tilde{\theta}) \geq M_\theta(\tilde{\theta}) := L_\theta(\tilde{\theta}) - C \max_{s_t} D_{KL}(\pi_\theta(\cdot|s_t)||\pi_{\tilde{\theta}}(\cdot|s_t))$$

where $C$ is some constant, $D_{KL}$ is the KL divergence between two probability distributions, and

$$L_\theta(\tilde{\theta}) = \mathbb{E}_{s_t \sim \rho_{\pi_\theta}, a_t \sim \pi_\theta} [A_{\pi_\theta}(s_t, a_t)]$$

$$\approx \mathbb{E}_{s_t \sim \rho_{\pi_\theta}, a_t \sim \pi_\theta} [A_{\pi_{\tilde{\theta}}}(s_t, a_t)].$$

Then, the surrogate function $M_\theta(\tilde{\theta})$ minimizing the original objective function $J(\tilde{\theta})$ is maximized. In TRPO \[11\], by making the subtraction term $\max_{s_t} D_{KL}(\pi_\theta(\cdot|s_t)||\pi_{\tilde{\theta}}(\cdot|s_t))$ in the surrogate function $M_\theta(\tilde{\theta})$ in \[3\] as a constraint, the unconstrained MM optimization is converted to a KL-divergence-constrained policy optimization with importance sampling which guarantees monotone improvement, given by \[11\]

$$\arg\max_{\tilde{\theta}} \mathbb{E}_{s_t \sim \rho_{\pi_{\tilde{\theta}}}, a_t \sim \pi_{\tilde{\theta}}} \left[ \frac{\pi_{\tilde{\theta}}(a_t|s_t)}{\pi_\theta(a_t|s_t)} A_{\pi_\theta}(s_t, a_t) \right]$$

s.t. $\mathbb{E}_{s_t \sim \rho_{\pi_{\tilde{\theta}}}} \left[ D_{KL}(\pi_\theta(\cdot|s_t)||\pi_{\tilde{\theta}}(\cdot|s_t)) \right] \leq \delta,$

with some constant $\delta$. Note that the step \[6\] is basically $\arg\max_{\tilde{\theta}} L_\theta(\tilde{\theta})$. Here, the expectation over $a_t \sim \pi_{\tilde{\theta}}$ in \[4\] is replaced with the expectation over $a_t \sim \pi_\theta$ in \[6\] by using the importance sampling technique, i.e., the importance sampling weight $\frac{\pi_{\tilde{\theta}}(a_t|s_t)}{\pi_\theta(a_t|s_t)}$ between the updated policy $\pi_{\tilde{\theta}}(a_t|s_t)$ and the old policy $\pi_\theta(a_t|s_t)$ is multiplied to the original term $A_{\pi_\theta}(s_t, a_t)$ for expectation. Note also that the maximization over $s_t, a_t, \max_{s_t} D_{KL}(\pi_\theta(\cdot|s_t)||\pi_{\tilde{\theta}}(\cdot|s_t))$ in \[3\], is replaced with the expectation over $s_t \sim \rho_{\pi_{\tilde{\theta}}}$. Thus, the expectations in both the objective function \[6\] and the KL divergence constraint \[7\] are over the states and actions generated by the available old policy $\pi_{\tilde{\theta}}$ and hence can be computed empirically by using samples in trajectories generated by the old policy $\pi_\theta$. (For real implementation, the advantage function $A_{\pi_{\tilde{\theta}}}(s_t, a_t)$ in \[6\] should also be replaced with a computable estimate.) TRPO updates $\tilde{\theta}$ to the natural gradient direction from the KL constraint and performs line search until the objective value increases.

C. Clipping Importance Sampling Weights

In TRPO, for the objective function \[6\], importance sampling is used to estimate the expectation over $\pi_{\tilde{\theta}}$ by using sample actions generated from the previous policy $\pi_{\tilde{\theta}}$. Since the sample average is not the true expectation, there can be a large difference between the optimization objective and the actual discounted reward sum when the weight $\frac{\pi_{\tilde{\theta}}(a_t|s_t)}{\pi_\theta(a_t|s_t)}$ for importance sampling is too large. In this case, TRPO can update $\tilde{\theta}$ to a wrong direction although there exists the KL distance constraint to restrict the amount of update from the old policy parameter $\theta$ and to the new parameter $\tilde{\theta}$. Due to such a drawback, TRPO cannot train many tasks of Mujoco games well \[16\]. In order to overcome this drawback and bound the size of update more effectively, PPO \[11\] proposes the clipping technique that clips the importance sampling weight $R_t(\tilde{\theta}) = \frac{\pi_{\tilde{\theta}}(a_t|s_t)}{\pi_\theta(a_t|s_t)}$ as follows:

$$\arg\max_{\tilde{\theta}} L_\theta^{CLIP}(\tilde{\theta}) = \mathbb{E}_{a_t \sim \rho_{\pi_\theta}, a_t \sim \pi_{\tilde{\theta}}} \left[ \min\{R_t(\tilde{\theta})\hat{A}_t, \ clip(R_t(\tilde{\theta}), 1 - \epsilon, 1 + \epsilon)\hat{A}_t\} \right],$$

where $\hat{A}_t$ is the sample estimated advantage function and

$$\text{clip}(R_t(\tilde{\theta}), 1 - \epsilon, 1 + \epsilon) = \max(\min(R_t(\tilde{\theta}), 1 + \epsilon), 1 - \epsilon).$$

PPO also considers the KL distance constraint as a penalty term in the objective function rather than a constraint, but simple PPO without the KL penalty term performs best in the Mujoco experiments. Hence, in this paper we consider the simple PPO. PPO outperforms TRPO significantly in most continuous action games since it effectively restricts wrong updates compared to TRPO. However, there still exist some games for which PPO performs worse than TRPO and this suggests that we need to consider more than the clipping technique for PPO.

1. Note that the Lagrangian of the constrained optimization \[6\] - \[7\] is the surrogate function $M_\theta(\tilde{\theta})$ with $C$ being the Lagrange multiplier, if the expectation operation in the constraint \[7\] is replaced with the original maximum operation.
III. MULTI-BATCH EXPERIENCE REPLAY

A. The Proposed Experience Replay Scheme

In PPO, clipping the importance sampling weights reduces the difference between the old policy and the new policy updated by stochastic gradient descent applied to (8), but it can also restrict positive updates. Furthermore, in PPO, the expectation in the objective function $L^{CLIP}_{\theta}(\hat{\theta})$ in (8) is estimated by the empirical average over a mini-batch of size $M$ from $N$ samples generated from the old policy $\pi_\theta$, and the gradient descents for policy update are performed based on multiple mini-batches from the same $N$ samples from $\pi_\theta$ and after the policy update, all $N$ samples from the old policy are discarded. Then, PPO collects new $N$ samples from the updated policy and exploits these new $N$ samples only for the next update. However, this is not an efficient way of using samples because the samples of the previous policies also contain information about the optimization and can be used for the policy update with importance sampling. In addition, PPO uses samples from the same trajectory of the previous policies to compute the advantage function required for the objective function (12). 

Thus, to overcome these disadvantages of PPO, we adopt the idea of experience replay used in DQN [6] and ACER [12] for policy optimization, which stores statistical information from multiple previous policies in an experience replay memory and draws sample mini-batches from the experience replay memory. However, we consider an experience replay scheme that is different from that used in DQN and ACER and is suitable for PPO-like policy gradient methods. To illustrate this, let us consider the Gaussian policy given by

$$a_{i,n} \sim \pi_{\theta_i}(\cdot|s_{i,n}) = \mathcal{N}(\mu_i(s_{i,n}; \phi_i), \sigma_i^2), \quad (10)$$

where $i$ is the policy update index, $\theta_i = (\phi_i, \sigma_i)$ is the policy parameter at the $i$-th policy update, and $N$ state-action pairs $(s_{i,1}, a_{i,1}), \ldots, (s_{i,N}, a_{i,N})$ are state-action samples generated from the policy $\pi_{\theta_i}$ at the $i$-th update. At the policy update time $i$, we store the statistical information $(s_{i',n}, a_{i',n}, \hat{A}_{i',n}, \hat{V}_{i',n}, \mu_{i'}, \sigma_{i'})$ for all $N$ samples from $n = 1, \ldots, N$ for each of the current and previous $L - 1$ policies $\pi_{\theta_{i'}}, i' = i, i - 1, \ldots, i - L - 1$ at the replay memory $R$, where $\hat{A}_{i,n}$ is the estimate of the advantage function of the $n$-th sample of the policy $\pi_{\theta_i}$, and $\hat{V}_{i,n}$ is the estimated target value computed by temporal difference (TD) $\lambda$ backup [4] required for advantage function estimation and will be explained in Section IV. Thus, the replay memory size is $NL$, where $L > 1$ is a small integer, and the replay memory stores the statistical information of the current and $L - 1$ previous policies:

$$R = \{(s_{i',n}, a_{i',n}, \hat{A}_{i',n}, \hat{V}_{i',n}, \mu_{i'}, \sigma_{i'}), i' = i, i - 1, \ldots, i - L - 1, n = 1, 2, \ldots, N\}. \quad (11)$$

Then, we sample a mini-batch of size $M$ randomly and uniformly from the $NL$ sample information stored in the replay memory $R$, and update the policy based on stochastic gradient descent with a modified importance sampling step for the policy index $i + 1$. Since the $M$ samples in a mini-batch are from the $NL$ samples of the $L$ different policies stored in $R$, the weight for importance sampling for the $m$-th sample in the mini-batch should be determined properly by considering the sample-generating policy index. Thus, the proposed optimization based on the application of the proposed experience replay scheme to PPO is given by

$$\arg\max_{\hat{\theta}} \bar{L}^{CLIP-ER}(\hat{\theta}) = \sum_{m=1}^{M} \alpha_m \min\{R_m(\hat{\theta}), \text{clip}(R_m(\hat{\theta}), 1 - \epsilon, 1 + \epsilon)\hat{A}_m\}, \quad (12)$$

where $\alpha_m$ is the weighting factor for the $m$-th sample such that $\alpha_m > 0$ and $\sum_{m=1}^{M} \alpha_m = 1$ and the importance sampling weight $R_m(\hat{\theta})$ for the $m$-th sample in the mini-batch is given by

$$R_m(\hat{\theta}) = \frac{\pi_{\theta}(a_m|s_m)}{\pi_{\theta_i(m)}(a_m|s_m)}. \quad (13)$$

For these multiple gradient descents, the $N$ samples from the old policy are shuffled in a random order and each block of consecutive $M$ samples from the shuffled $N$ samples is sequentially taken as one mini-batch in PPO. Then, $N/M$ gradient descents can be performed from the $N$ samples of the old policy. These $N/M$ gradient descents comprise one epoch.

The weighting factor $\alpha_m$ can be designed properly by considering the importance of the $m$-th sample. For simplicity, we can use $\alpha_m = 1/M$, $\forall m = 1, 2, \ldots, M$. 
Here, \( i(m) \) is the index of the policy that generated the \( m \)-th sample in the mini-batch. Finally, for the policy update for index \( i + 1 \), multiple updates based on stochastic gradient descent with multiple mini-batches of all size \( M \) drawn independently from the experience replay memory \( R \) are performed to increase the sample efficiency. Note that the proposed experience replay scheme can be applied to most policy gradient algorithms based on sample statistics.

**B. Advantages of the Proposed Experience Replay Scheme**

As mentioned in the previous subsection, in the proposed experience replay structure, the replay memory \( R \) stores samples with statistics from the current and previous \( L - 1 \) policies and each of the \( L \) policies produces \( N \) samples by batch. This structure makes a difference from the experience replay scheme used in DQN and ACER, and gives several advantages in policy optimization with importance sampling as compared to PPO and TRPO.

Furthermore, for the proposed structure we set the batch size \( N \) to be rather large in the order of thousand as in TRPO and PPO, but choose \( L \) as a small integer larger than or equal to two to harness benefits.

First, let us compare the proposed scheme with PPO. Suppose that the total samples obtained from the environment during the entire learning period is \( S = JN \). Consider PPO that updates the policy every \( N \) samples. For the update, PPO extracts a mini-batch of size \( M(< N) \) randomly from the \( N \) samples generated from the current policy, applies gradient descent to the policy based on the mini-batch, and repeats this mini-batch gradient descent multiple times to obtain a new policy for the next \( N \) samples. In this PPO case, we have \( J \) new policies and \( \frac{JN}{M} \) gradient descents (on average) for the entire learning period of \( S \) samples, if each sample is contained in a mini-batch only once on average (i.e., for one epoch of updates). Next consider PPO that updates the policy every \( LN \) samples with the same mini-batch size of \( M \). In this case, we have \( J/L \) new policies and \( \frac{JLN}{M} \) gradient descents (on average) for the entire learning period of \( S \) samples, if each sample is contained in a mini-batch only once on average. Comparing these two PPO cases, we observe that the latter case has a larger sample pool of size \( LN \) and hence the mini-batch of size \( M \) drawn randomly from the pool of \( LN \) samples has less correlation among the mini-batch samples to yield a positive effect. However, in the latter case, we have only \( J/L \) new policies over the entire learning period, whereas we have more frequent \( J \) new policies in the former case and hence samples used for update are from more frequently updated policies and therefore better in the former case. This yields an advantage to the former case. Thus, there exists a trade-off between the two effects and there exists an optimal policy update period \( N^* \) (in the unit of samples) for PPO. Let the corresponding number of policy updates be \( J^* \) such that \( J^*N^* = S \). Now, consider the proposed experience replay scheme applied to PPO with the policy update period of \( N^* \) with \( L \geq 2 \). In the proposed scheme, \((L - 1)N^* \) samples of the previous \( L - 1 \) policies are used together with \( N^* \) samples from the current policy to construct a pool of \( LN^* \) samples from which a mini-batch of size \( M \) is randomly drawn. Hence, the correlation among the samples in the mini-batch is reduced compared to PPO with the policy update period of \( N^* \) not only because the sample pool size is increased by factor \( L \) but also because \( LN^* \) are from \( L \) different policies. If each sample in the sample pool of size \( LN^* \) is contained in a mini-batch only once on average as before, we have \( \frac{LN^*}{M} \) gradient descents (on average) applicable for one policy update period. However, the policy update period with the proposed experience replay scheme is still \( N^* \), which is the same as that of PPO, and hence new policies are obtained as frequently as PPO with the policy update period of \( N^* \). Note that the number of gradient descents for the proposed scheme is \( J^* \frac{LN^*}{M} \) for the entire learning period, which is \( L \) times larger than that of PPO. Thus, the sample efficiency is increased by factor \( L \) when the proposed experience replay scheme is applied to original PPO. The reduced mini-batch sample correlation and increased sample efficiency together with the same policy update frequency yield fast convergence and stability of convergence as compared to original PPO.

Second, let us compare the proposed experience replay scheme with those of DQN and ACER. As already mentioned, for the proposed experience replay scheme, we use a relatively large batch size \( N \) in the order of thousand as in TRPO and PPO and a small \( L \) (\( \geq 2 \)). With this multi-batch experience replay memory with a few policies, the bias resulting from clipping importance sampling ratios is not so significant. On the contrary, the experience replay memory of DQN or ACER contains samples of many policies. Typically, DQN generates one sample by one policy, pushes the newest samples into the experience replay memory, discards the oldest samples from the experience replay memory, and updates the policy based on a mini-batch from the experience memory. Note the proposed experience replay scheme can be applied to most policy gradient algorithms based on sample statistics.
replay memory. ACER generates a mini-batch of samples by one policy and stores many such mini-batches in the experience replay memory, and picks a mini-batch from the experience replay memory to update the policy. Thus, for both DQN and ACER, the first sample in the experience replay memory is from the oldest policy, the last sample is from the newest policy, and hence the policy statistics of the first sample and the last sample can be very different for the experience replay schemes used in DQN or ACER. Policy statistics are irrelevant to DQN since DQN only considers states, actions and rewards in the experience replay memory without using the statistics in off-policy update. However, in the case of ACER, the aforementioned difference in policy statistics yields large bias when clipping of importance sampling weights is applied. Thus, ACER corrects the bias term from clipping. On the contrary, with our proposed experience replay scheme with batch samples from only a few policies, the statistics of all the samples in the experience replay memory are not different much. Therefore, the bias from clipping of importance sampling ratios is insignificant with the proposed multi-batch experience replay scheme. Furthermore, ACER cannot choose random samples from the overall experience replay memory for mini-batch construction but it should use consecutive samples from the sample policy in the experience replay memory for computation of the retrace Q-value since ACER computes the retrace Q-value after mini-batch extraction by using the instantaneous reward in the experience replay memory. On the contrary, the proposed experience replay scheme precomputes the advantage function and the target value and stores those values instead of the instantaneous reward in the experience replay memory and hence it can choose arbitrary random samples in the experience replay memory. Thus, it can reduce the mini-batch sample correlation. The sample generation and mini-batch construction of PPO, PPO-ER and ACER are illustrated in Fig. 1.

Third, the proposed multi-batch experience replay scheme automatically gives priority to more important samples due to its batch structure. Note that DQN and ACER with experience replay perform mini-batch updates by using very old and new samples with equal weight. Hence, convergence is slow since the statistics of old samples are far from the optimal policy until the policy nearly approaches the optimal one, as seen in the comparison of ACER and PPO [1]. However, the multi-batch experience replay with large $N$ and small $L$ discards samples from too old policies and the policy updates are based on samples generated from recent policies and this makes the speed of convergence fast.
IV. THE ALGORITHM

Now, we present the proposed modification of PPO with the proposed experience replay scheme applied. The algorithm basically maximizes the objective function \( \hat{L}^{\text{CLIP-ER}}(\tilde{\theta}) \) defined in \([12]\) in Section III-A. To compute \( \hat{L}^{\text{CLIP-ER}}(\tilde{\theta}) \), we need an estimate the advantage function for each sample \( m \) in each mini-batch. For this, estimates of the advantage functions \( A_{\tilde{\theta}^i,n} \), \( i' = i, i - 1, \ldots, i - L + 1, n = 1, 2, \ldots, N \) for samples \( n = 1, 2, \ldots, N \) of each of the policies \( \pi_{\theta_i} \), \( i' = i, i - 1, \ldots, i - L + 1 \) are precomputed and stored in the replay memory \( R \) as in \([11]\). For the computation of \( A_{\tilde{\theta}^i,n} \), we just apply the generalized advantage estimator \( A_{\tilde{\theta}^i,n} \) used in PPO \([17]\) based on TD learning with parameter \( \lambda \) from the \( N \) collected samples from the policy \( \pi_{\theta_i} \) \([4], [13]\):

\[
\hat{A}_{\tilde{\theta}^i,n} = \sum_{l=0}^{N-n-1} (\gamma \lambda)^l \delta_{\tilde{v},l+n}, \quad i' = i, i - 1, \ldots, i - L + 1, \quad n = 1, \ldots, N,
\]

where \( \delta_{\tilde{v},l} = r_{\tilde{v},l} + \gamma V_{\pi_{\theta_i}}(s_{\tilde{v},l+1}) - V_{\pi_{\theta_i}}(s_{\tilde{v},l}) \). Here, \( s_{\tilde{v},l} \) is the state of sample \( l \) generated by the policy \( \pi_{\theta_i} \), \( r_{\tilde{v},l} \) is the corresponding reward at sample time \( l \), and \( V_{\pi_{\theta_i}}(s_{\tilde{v},l}) \) is the state value function of the state \( s_{\tilde{v},l} \) under the policy \( \pi_{\theta_i} \), which is approximated by a neural network. For the update of this neural network, we need to compute and store the TD(\( \lambda \)) target value \( \hat{V}_{\tilde{v},n} \) given by

\[
\hat{V}_{\tilde{v},n} = \hat{A}_{\tilde{v},n} + V_{\pi_{\theta_i}}(s_{\tilde{v},n}), \quad i' = i, i - 1, \ldots, i - L + 1, \quad n = 1, \ldots, N.
\]

Hence, for continuous control, we use two neural networks:

(i) the policy network: in the case of Gaussian policy \( \sigma \sim \pi_{\theta_i} (s) = N(\mu(s; \phi), \sigma^2) \). In general, the mean of the Gaussian is implemented by using a mean neural network \( \mu(s; \phi) \) taking state \( s \) as the input with the mean network parameter \( \phi \) and the variance is given by the single parameter \( \sigma \). Thus, the mean parameter \( \phi \) and the variance parameter \( \sigma \) comprise the policy parameter \( \pi_{\theta_i} = (\phi, \sigma) \).

(ii) the value network \( V_{\theta_i} \): This neural network is required and used to compute the advantage function estimate \([14]\) and the target value \([15]\). The value network is updated to minimize the mean square error between the network output value and the target value, i.e., to minimize \( \hat{L}^V(\hat{V}_i) = \frac{1}{M} \sum_{m=0}^{M-1} (V_{\theta_i}(s_m) - \hat{V}_m)^2 \), where \( s_m \) and \( \hat{V}_m \) are the state and TD(\( \lambda \)) target value of the \( m \)-th sample in the mini-batch of size \( M \) drawn randomly from the \( NL \) samples in the replay memory.

By defining the overall parameter \( \theta_{\text{OVERALL}} \) combining the policy parameter \( \theta_{\text{POLICY}} \) and the value parameter \( \theta_{\text{VALUE}} \), we obtain the generalized objective function defined as \([11]\)

\[
\arg\max_{\theta_{\text{OVERALL}}} \hat{L}(\theta_{\text{OVERALL}}) = \hat{L}^{\text{CLIP-ER}}(\theta_{\text{POLICY}}) - c \hat{L}^V(\theta_{\text{VALUE}}),
\]

where \( c(>0) \) is constant. In some cases, the policy network \( \theta_{\text{POLICY}} \) and value network \( \theta_{\text{VALUE}} \) share a portion of network and the corresponding parameter as in \([13]\). Then, the combined generalized objective function is meaningful. In the case in which the policy network and value network do not share any portion, the optimization \([16]\) can simply be performed separately over \( \theta_{\text{POLICY}} \) and \( \theta_{\text{VALUE}} \). In this paper, we assume the latter case with \( c = 1 \); the two networks do not share the parameter.

We consider \( K \) actors to gather sample trajectories from parallel environments as \([11]\). Each actor collects \( N/K \) samples from the current policy to yield \( N \) samples for the current policy; compute the estimate of the advantage function \([14]\) and the empirical return \([15]\); and store the trajectories with the stochastic information to the experience replay memory. Then, we sample a mini-batch of size \( M \) from the replay memory of \( NL \) samples to compute \( \theta_{\text{OVERALL}} \) in \([16]\) and update the parameter to the stochastic gradient direction. The algorithm is summarized as Algorithm \([11]\) named proximal policy optimization with (multi-batch) experience replay (PPO-ER).
Algorithm 1 Proximal Policy Optimization with (Multi-Batch) Experience Replay (PPO-ER)

Require: $N$: size of a batch, $M$: size of a mini-batch, $L$: replay policy depth, $K$: number of actors, $\beta$: step size

1: for $i = 1, 2, \cdots$ (policy index) do
2: for $k = 1, 2, \cdots, K$ (actor index) (parallel processing of the $K$ actors) do
3: Collect a trajectory $(s_{i,1}^{(k)}, a_{i,1}^{(k)}, r_{i,1}^{(k)}, \cdots, s_{i,N/K}^{(k)}, a_{i,N/K}^{(k)}, r_{i,N/K}^{(k)})$ from the $i$-th policy $\pi_{\theta_i}$. 
4: Estimate advantage functions $\hat{A}_{i,1}^{(k)}, \cdots, \hat{A}_{i,N/K}^{(k)}$ from the $N/K$ samples.
5: Estimate target values $\hat{V}_{i,1}^{(k)}, \cdots, \hat{V}_{i,N/K}^{(k)}$ from the $N/K$ samples.
6: Store all samples and statistics $(s_{i,n}^{(k)}, a_{i,n}^{(k)}, \hat{A}_{i,n}^{(k)}, \hat{V}_{i,n}^{(k)}, \mu_i^{(k)}, \sigma_i^{(k)})$ at the replay memory $R_k$ for actor $k$ with size $NL/K$ samples.
7: end for
8: for epoch = 1, 2, \cdots, $T$ do
9: for $j = 1, 2, \cdots, NL/M$ (mini-batch index) do
10: for $k = 1, 2, \cdots, K$ (actor index) (parallel processing of the $K$ actors) do
11: Draw $M/K$ samples randomly from $R_k$. 
12: end for
13: Collect all the samples of the $K$ actors to construct a mini-batch of size $M$. 
14: Update the parameter as $\theta_{OVERALL,i+1} \leftarrow \theta_{OVERALL,i} + \beta \nabla \tilde{\theta}_{OVERALL} \tilde{L}(\tilde{\theta}_{OVERALL})$ from the mini-batch. 
15: end for
16: end for
17: end for

V. EXPERIMENTS: PERFORMANCE COMPARISON ON CONTINUOUS ACTION CONTROL TASKS

To evaluate our algorithm, we performed simulations on Mujoco physics engines [16], classic control, and Box2D [19] in OpenAI GYM [20]. The continuous action dimensions and state dimensions of each task are described by

| Table I | DESCRIPTION OF CONTINUOUS ACTION CONTROL TASKS |
|---------|---------------------------------------------|
| **Mujoco Tasks** | State dim. | Action dim. |
| HalfCheetah-v1 | 17 | 6 |
| Hopper-v1 | 11 | 3 |
| HumanoidStandup-v1 | 376 | 17 |
| Humanoid-v1 | 376 | 17 |
| InvertedDoublePendulum-v1 | 11 | 1 |
| InvertedPendulum-v1 | 4 | 1 |
| Swimmer-v1 | 8 | 2 |
| Reacher-v1 | 11 | 2 |
| Walker2d-v1 | 17 | 6 |
| **Classic Control** | State dim. | Action dim. |
| Pendulum-v0 | 3 | 1 |
| **Box2D** | State dim. | Action dim. |
| BipedalWalker-v2 | 24 | 4 |
| BipedalWalkerHardcore-v2 | 24 | 4 |

We compared our algorithm with PPO and TRPO for above the various continuous action control tasks in Table I. We used the Adam optimizer [21] for stochastic gradient descent and set the hyperparameters of PPO-ER to be the same as those of of PPO on Mujoco tasks. The Adam step size $\beta$ and the clipping factor $\epsilon$ in (9) were linearly annealed from 1 to 0 as the time step continued, as described in [1]. We used $L = 2$ for the experience replay memory$^5$ Fig. 2 shows the results. It is seen that PPO-ER converges faster and achieves higher scores than TRPO and PPO on most of the considered continuous control tasks in both single-actor and multi-actor cases.

$^5$We observed that increasing the replay memory size more than $L = 2$ does not improve the performance much.
TABLE II

PPO-ER HYPERPARAMETERS FOR CONTINUOUS CONTROL TASKS

| Hyperparameter         | Value       |
|------------------------|-------------|
| Horizon \( (N) \)      | 2048        |
| Mini-batch size \( (M) \) | 64          |
| Num. of actors \( (K) \) | 1 or 8      |
| Clipping factor \( (\epsilon) \) | 0.2\( \alpha \) |
| Step size \( (\beta) \) | 3 \cdot 10^{-4} \( \alpha \) |
| Epochs                | 10          |
| Discount factor \( (\gamma) \) | 0.99       |
| TD parameter \( (\lambda) \) | 0.95       |

VI. CONCLUSION

In this paper, a multi-batch experience replay scheme is proposed to enhance the performance of off-policy actor-critic-style policy gradient methods such as PPO. The proposed experience replay scheme with a relatively large
batch size but a small number of batches in the replay memory increases the speed and stability of convergence by 1) reducing the correlation of mini-batch samples, 2) increasing the sample efficiency, 3) maintaining the statistical distance among the samples in the replay memory small and hence 4) preventing large importance sampling weights. Numerical results show that the proposed experience replay scheme applied to PPO improves the performance on various continuous control tasks (Mujoco tasks, classic control, and Box2d on OpenAI GYM) compared to original PPO and TRPO in terms of both the convergence speed and the global convergence. The proposed experience replay scheme can be used for general off-policy actor-critic-style algorithms based on sample statistics.

REFERENCES

[1] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, “Proximal policy optimization algorithms,” arXiv preprint arXiv:1707.06347, 2017.
[2] C. J. Watkins and P. Dayan, “Q-learning,” Machine Learning, vol. 8, no. 3, pp. 279–292, 1992.
[3] G. A. Rummery and M. Niranjan, On-line Q-learning using connectionist systems, vol. 37. University of Cambridge, Department of Engineering, 1994.
[4] R. S. Sutton and A. G. Barto, Reinforcement learning: An introduction. Cambridge, MA: The MIT Press, 1998.
[5] A. Geramifard, T. J. Walsh, S. Tellex, G. Chowdhary, N. Roy, and J. P. How. A Tutorial on Linear Function Approximators for Dynamic Programming and Reinforcement Learning. Now, 2013.
[6] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller, “Playing atari with deep reinforcement learning,” arXiv preprint arXiv:1312.5602, 2013.
[7] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al., “Human-level control through deep reinforcement learning,” Nature, vol. 518, no. 7540, pp. 529–533, 2015.
[8] R. S. Sutton, D. A. McAllester, S. P. Singh, and Y. Mansour, “Policy gradient methods for reinforcement learning with function approximation,” in Advances in Neural Information Processing Systems, pp. 1057–1063, 2000.
[9] S. Amari, “Natural gradient works efficiently in learning,” Neural Comput., pp. 251 – 276, 1998.
[10] S. M. Kakade, “A natural policy gradient,” in Advances in Neural Information Processing Systems, pp. 1531–1538, 2002.
[11] J. Schulman, S. Levine, P. Abbeel, M. Jordan, and P. Moritz, “Trust region policy optimization,” in Proceedings of the 32nd International Conference on Machine Learning (ICML-15), pp. 1889–1897, 2015.
[12] Z. Wang, V. Bapst, N. Heess, V. Mnih, R. Munos, K. Kavukcuoglu, and N. de Freitas, “Sample efficient actor-critic with experience replay,” arXiv preprint arXiv:1611.01224, 2016.
[13] L. C. Baird, “Reinforcement learning in continuous time: Advantage updating,” in Neural Networks, 1994. IEEE World Congress on Computational Intelligence., 1994 IEEE International Conference on, vol. 4, pp. 2448–2453, IEEE, 1994.
[14] D. R. Hunter and K. Lange, “A tutorial on MM algorithms,” The American Statistician, pp. 30 – 37, Feb. 2004.
[15] S. Kakade and J. Langford, “Approximately optimal approximate reinforcement learning,” in ICML, vol. 2, pp. 267–274, 2002.
[16] E. Todorov, T. Erez, and Y. Tassa, “Mujoco: A physics engine for model-based control,” in Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on, pp. 5026–5033, IEEE, 2012.
[17] J. Schulman, P. Moritz, S. Levine, M. Jordan, and P. Abbeel, “High-dimensional continuous control using generalized advantage estimation,” arXiv preprint arXiv:1506.02438, 2015.
[18] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu, “Asynchronous methods for deep reinforcement learning,” in International Conference on Machine Learning, pp. 1928–1937, 2016.
[19] E. Catto, “Box2d: A 2d physics engine for games,” 2011.
[20] G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba, “Openai gym,” arXiv preprint arXiv:1606.01540, 2016.
[21] D. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.