CaRe-BN: Precise Moving Statistics for Stabilizing Spiking Neural Networks in Reinforcement Learning

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Abstract

Spiking Neural Networks (SNNs) offer low-latency and energy-efficient decision-making on neuromorphic hardware by mimicking the event-driven dynamics of biological neurons. However, due to the discrete and non-differentiable nature of spikes, directly trained SNNs rely heavily on Batch Normalization (BN) to stabilize gradient updates. In online Reinforcement Learning (RL), imprecise BN statistics hinder exploitation, resulting in slower convergence and suboptimal policies. This challenge limits the adoption of SNNs for energy-efficient control on resource-constrained devices. To overcome this, we propose Confidence-adaptive and Re-calibration Batch Normalization (CaRe-BN), which introduces (*i*) a confidence-guided adaptive update strategy for BN statistics and (*ii*) a re-calibration mechanism to align distributions. By providing more accurate normalization, CaRe-BN stabilizes SNN optimization without disrupting the RL training process. Importantly, CaRe-BN does not alter inference, thus preserving the energy efficiency of SNNs in deployment. Extensive experiments on continuous control benchmarks demonstrate that CaRe-BN improves SNN performance by up to 22.6% across different spiking neuron models and RL algorithms. Remarkably, SNNs equipped with CaRe-BN even surpass their ANN counterparts by 5.9%. These results highlight a new direction for BN techniques tailored to RL, paving the way for neuromorphic agents that are both efficient and high-performing.

1 Introduction

Spiking Neural Networks (SNNs) have emerged as a promising class of neural models that more closely mimic the event-driven computation of biological brains (Maass, 1997; Gerstner et al., 2014). This event-driven property makes SNNs particularly well suited for deployment on neuromorphic hardware platforms (Davies et al., 2018; DeBole et al., 2019), enabling low-latency and energy-efficient inference.

In parallel, Reinforcement Learning (RL) has achieved remarkable success across a wide range of domains (Mnih et al., 2015b; Lillicrap et al., 2015; Haarnoja et al., 2018). Among these, continuous control tasks have received significant attention due to their alignment with real-world scenarios and their strong connection to embodied AI and robotic applications (Kober et al., 2013; Gu et al., 2017; Brunke et al., 2022). Combining the strengths of SNNs with RL (SNN-RL) offers the potential to train agents that not only learn complex behaviors but also execute them with extremely low energy consumption (Yamazaki et al., 2022). This makes SNN-RL particularly appealing for robotics and autonomous systems deployed on resource-constrained edge devices.

However, training SNNs is challenging. Due to their discrete dynamics and non-differentiable activation functions, SNNs are heavily dependent on Batch Normalization (BN) (Ioffe & Szegedy, 2015) to mitigate gradient vanishing or explosion. BN stabilizes optimization by normalizing activations with moving estimates of the mean and variance, thereby alleviating temporal covariate shifts in SNNs and enabling state-of-the-art performance (Duan et al., 2022; Jiang et al., 2024).

While effective in supervised learning, BN suffers a severe breakdown in online RL because moving statistics cannot be estimated precisely under nonstationary dynamics. As shown in Figure 1, traditional BN struggles to track the true statistics: When distributions shift rapidly (Figure 1(a)),

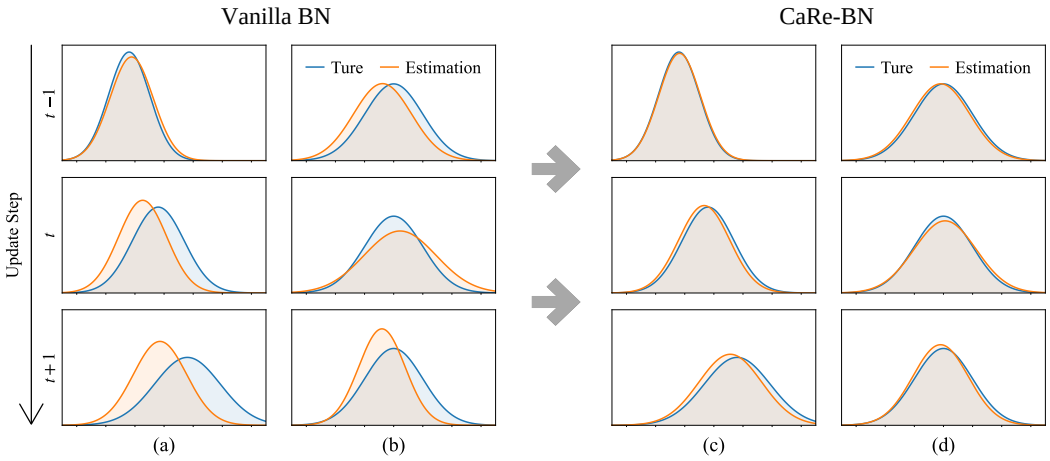

Figure 1: Real and estimated input activation distributions in BN layers. Distributions change rapidly in (a) and (c), while remaining stable in (b) and (d).

estimates lag behind; when distributions are relatively static (Figure 1(b)), estimates contain noise. These inaccuracies lead agents to select suboptimal actions and generate poor trajectories, which are then reused for training—further compounding the problem and hindering policy improvement.

In this work, we address this issue by proposing **Confidence-adaptive and Re-calibration Batch Normalization** (CaRe-BN), a BN strategy tailored for SNN-based RL. CaRe-BN introduces two complementary components: (*i*) **Confidence-adaptive update** (Ca-BN), a confidence-weighted moving estimator of BN statistics that ensures unbiasedness and optimal variance reduction; and (*ii*) **Re-calibration** (Re-BN), a periodic correction scheme that leverages replay buffer resampling to refine inference statistics. Together, these mechanisms enable precise, low-variance estimation of BN statistics under the nonstationary dynamics of SNN-RL (Figure 1). With more accurate moving statistics, CaRe-BN stabilizes SNN optimization **without disrupting the online RL process**.

We evaluate CaRe-BN on various continuous control tasks from MuJoCo (Todorov et al., 2012; Todorov, 2014b). The results show that CaRe-BN not only resolves the issue of imprecise BN statistics but also accelerates training and achieves state-of-the-art performance. Remarkably, SNN-based agents equipped with CaRe-BN even **outperform their ANN counterparts by 5.9%**, without requiring complex neuron dynamics or specialized RL frameworks.

2 Related Works

2.1 Batch Normalization in Spiking Neural Networks

Batch Normalization (BN) was originally proposed for ANNs to mitigate internal covariate shift during training (Ioffe & Szegedy, 2015), thereby accelerating convergence and improving performance (Santurkar et al., 2018). To address unstable training in SNNs, several extensions of BN have been developed (Zheng et al., 2021; Duan et al., 2022; Kim & Panda, 2021; Jiang et al., 2024). While these methods are effective in supervised tasks, they are designed under the assumption of static training–inference distributions. This assumption is violated in online RL, where distributions shift continually as the agent interacts with the environment, making these BN variants ill-suited for SNN-RL.

2.2 Spiking Neural Networks in Reinforcement Learning

Early work in SNN-RL primarily relied on synaptic plasticity rules, particularly reward-modulated Spike-Timing-Dependent Plasticity (R-STDP) and its variants (Florian, 2007; Frémaux & Gerstner, 2016; Gerstner et al., 2018; Frémaux et al., 2013; Yang et al., 2024). Another research direction focused on ANN-to-SNN conversion: Patel et al. (2019); Tan et al. (2021); Kumar et al. (2025)

converted Deep Q-Networks (DQNs) (Mnih, 2013; Mnih et al., 2015a) into SNNs. To enable direct gradient-based training, Liu et al. (2022); Chen et al. (2022); Qin et al. (2022); Sun et al. (2022) applied Spatio-Temporal Backpropagation (STBP) (Wu et al., 2018) to train DQNs, while Bellec et al. (2020) introduced e-prop with eligibility traces to train policy networks using policy gradient methods (Sutton et al., 1999).

For continuous control tasks, hybrid frameworks have been extensively explored (Tang et al., 2020; 2021; Zhang et al., 2022; Chen et al., 2024a; Zhang et al., 2024; Ding et al., 2022; Chen et al., 2024b; Xu et al., 2025). These approaches typically employ a Spiking Actor Network (SAN) co-trained with a deep ANN critic in the Actor–Critic framework (Konda & Tsitsiklis, 1999). However, none of these methods address the challenge of normalization in SNN-based RL. The absence of proper normalization often leads to unstable updates, slower convergence, or even divergence during training.

3 PRELIMINARIES

3.1 SPIKING NEURAL NETWORKS

Spiking Neural Networks (SNNs) communicate through discrete spikes rather than continuous activations. The most widely used neuron model is the Leaky Integrate-and-Fire (LIF) neuron, whose membrane potential dynamics are described as:

$$H_t = \lambda V_{t-1} + C_t, \qquad S_t = \Theta(H_t - V_{th}), \qquad V_t = (1 - S_t) \cdot H_t + S_t \cdot V_{\text{reset}}, \tag{1}$$

where C_t, H_t, S_t, and V_t denote the input current, the accumulated membrane potential, the binary output spike, and the post-firing membrane potential at time step t, respectively. The parameters V_{th}, V_{reset}, and λ represent the firing threshold, reset voltage, and leakage factor, respectively. $\Theta(\cdot)$ is the Heaviside step function.

3.2 REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a framework in which an agent learns to maximize cumulative rewards by interacting with an environment. The agent maps states (or observations) to actions, with the learning loop consisting of two steps: ***(i)*** the agent selects an action, receives a reward, and transitions to the next state; and ***(ii)*** the agent updates its policy by sampling mini-batches of past experiences.

Because the policy continuously evolves during training, the data distribution is inherently non-stationary. This poses challenges for batch normalization methods, which rely on the assumption of a stationary distribution.

3.3 BATCH NORMALIZATION

Batch Normalization (BN) (Ioffe & Szegedy, 2015) is a widely used technique to stabilize and accelerate the training of deep neural networks. Given an activation $x_i \in \mathbb{R}^d$ at iteration i, BN normalizes it using the mean and variance computed over a mini-batch $\mathcal{B} = \{x_i^1, \ldots, x_i^N\}$:

$$\mu_{\mathcal{B}} = \frac{1}{N}\sum_{j=1}^{N} x_i^j, \quad \sigma_{\mathcal{B}}^2 = \frac{1}{N}\sum_{j=1}^{N}(x_i^j - \mu_{\mathcal{B}})^2, \tag{2}$$

$$\hat{x}_i = \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}}, \quad y_i = \gamma \hat{x}_i + \beta, \tag{3}$$

where ϵ is a small constant for numerical stability, and γ, β are learnable affine parameters. During inference, moving statistics $(\hat{\mu}_i, \hat{\sigma}_i^2)$ are used in place of batch statistics (μ_i, σ_i^2).

In supervised learning, this discrepancy between training (mini-batch statistics) and inference (moving statistics) is usually tolerable, as imprecise moving estimates do not directly affect gradient updates. However, in online RL, inaccurate moving statistics degrade policy exploitation, leading to unstable training dynamics and even divergence.

4 METHODOLOGY

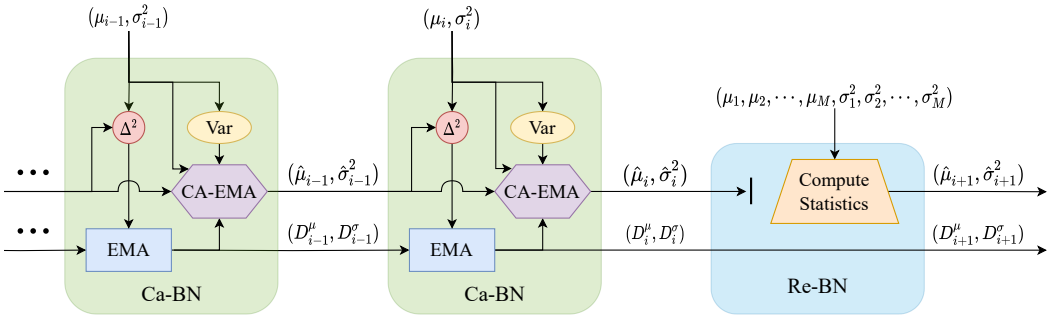

Figure 2: The statistics estimation scheme of CaRe-BN. In this framework, Ca-BN is applied at every update step, while Re-BN is performed periodically. Δ^2 denotes the squared error, **Var** represents the variance computed according to Eq. 9, **EMA** refers to the exponential moving average in Eq. 12, and **CA-EMA** denotes the confidence-adaptive update defined in Eqs. 5 and 6.

As illustrated in Figure 2, we propose Confidence-adaptive and Recalibration Batch Normalization (CaRe-BN) to address the challenge of approximating moving statistics in online RL. Section 4.1 analyzes the limitations of traditional BN in online RL, where statistics are often estimated imprecisely. Section 4.2 introduces the confidence-adaptive update mechanism (Ca-BN), which dynamically adjusts statistics estimation based on the reliability of the current approximation. Section 4.3 presents the recalibration mechanism (Re-BN), which periodically corrects accumulated estimation errors. Finally, Section 4.4 integrates these components into the full CaRe-BN framework and demonstrates its use in online RL algorithms.

4.1 ISSUES IN APPROXIMATING MOVING STATISTICS

Online RL introduces stronger distribution shifts. Unlike supervised learning, where the data distribution is typically assumed to be static, online RL involves continuous interaction between the agent and the environment. This results in a non-stationary data distribution, which in turn causes activation statistics to drift over time.

Inaccurate statistics degrade RL performance. Supervised learning only requires the final moving statistics to be accurate, as inference is performed after training. In contrast, online RL requires reliable statistics throughout training. When statistics are imprecise, the agent selects suboptimal actions during exploration and exploitation, generating poor trajectories that further degrades policy updates.

The key of the problem lies in accurately estimating inference-time statistics under shifting distributions. Hence, it is essential to design estimators that adapt to distributional changes while minimizing approximation error during training.

It is worth noting that most conventional ANN-based RL algorithms do not employ BN (Lillicrap, 2015; Sutton & Barto, 2018), as shallow ANNs can often learn stable representations without normalization. In contrast, BN is indispensable for stabilizing SNNs training. Therefore, addressing this issue is particularly critical for SNN-based RL.

4.2 CONFIDENCE-ADAPTIVE UPDATE OF BN STATISTICS (CA-BN)

Conventional BN approximates population statistics using an exponential moving average (EMA) of the batch mean and variance:

$$\hat{\mu}_i \leftarrow (1-\alpha)\hat{\mu}_{i-1} + \alpha\mu_i, \quad \hat{\sigma}^2_i \leftarrow (1-\alpha)\hat{\sigma}^2_{i-1} + \alpha\sigma^2_i, \tag{4}$$

where α is the momentum parameter. This update rule faces a fundamental **noise–delay trade-off**. As shown in Figure 1, low momentum yields stable but slow adaptation to distribution shifts, while

high momentum adapts quickly but amplifies the noise from small-batch estimates. This trade-off is particularly harmful in online RL, where accurate normalization is critical for stable policy learning.

Inspired by the Kalman estimator (Kalman, 1960), we derive a confidence-guided mechanism that adaptively reweights estimators to minimize the mean-squared error (MSE) of BN statistics.

Theorem 1 *Let (μ_i, σ_i^2) and $(\hat{\mu}_{i|i-1}, \hat{\sigma}^2_{i|i-1})$ be two unbiased estimators of the population parameters (μ_i^*, σ_i^{*2}). The optimal linear estimator that minimizes MSE is*

$$\hat{\mu}_i = (1 - K_i^\mu)\hat{\mu}_{i|i-1} + K_i^\mu \mu_i, \qquad K_i^\mu = \frac{\mathbb{D}(\mu_i^* - \hat{\mu}_{i|i-1})}{\mathbb{D}(\mu_i^* - \hat{\mu}_{i|i-1}) + \mathbb{D}(\mu_i^* - \mu_i)}, \tag{5}$$

$$\hat{\sigma}_i^2 = (1 - K_i^\sigma)\hat{\sigma}^2_{i|i-1} + K_i^\sigma \sigma_i^2, \qquad K_i^\sigma = \frac{\mathbb{D}(\sigma_i^{*2} - \hat{\sigma}^2_{i|i-1})}{\mathbb{D}(\sigma_i^{*2} - \hat{\sigma}^2_{i|i-1}) + \mathbb{D}(\sigma_i^{*2} - \sigma_i^2)}, \tag{6}$$

where K_i^μ and K_i^σ are confidence-guided adaptive weights, and $\mathbb{D}(\cdot)$ denotes estimation variance (the reciprocal of confidence).

Proof 1 *Since both $\hat{\mu}_{i|i-1}$ and μ_i are unbiased for μ_i^*, any linear combination $\tilde{\mu}_i = (1-K)\hat{\mu}_{i|i-1} + K\mu_i$ is also unbiased. The variance is*

$$\mathbb{D}(\tilde{\mu}_i - \mu_i^*) = (1 - K)^2 \cdot \mathbb{D}(\hat{\mu}_{i|i-1} - \mu_i^*) + K^2 \cdot \mathbb{D}(\mu_i - \mu_i^*). \tag{7}$$

Minimizing over K yields the optimal $K = K_i^\mu$. The variance update (Eq. 6) follows analogously.

Assumption 1 *The activations in iteration i are modeled as $x_i \sim \mathcal{N}(\mu_i^*, \sigma_i^{*2})$, following the standard Gaussianity assumption in BN.*

Confidence of mini-batch statistics. For a batch of size N, the sample mean μ_i and variance σ_i^2 satisfy

$$\mu_i \sim \mathcal{N}\left(\mu_i^*, \tfrac{\sigma_i^{*2}}{N}\right), \qquad \frac{(N-1)\sigma_i^2}{\sigma_i^{*2}} \sim \chi^2_{N-1}. \tag{8}$$

Since μ_i and σ_i^2 are unbiased estimators of μ_i^* and σ_i^{*2}, we approximate

$$\mathbb{D}(\mu_i^* - \mu_i) = \frac{\sigma_i^{*2}}{N} \approx \frac{\sigma_i^2}{N}, \qquad \mathbb{D}(\sigma_i^{*2} - \sigma_i^2) = \frac{2\sigma_i^{*4}}{N-1} \approx \frac{2\sigma_i^4}{N-1}. \tag{9}$$

Confidence of previous estimates. Since the true distribution drift is unknown, we approximate

$$\hat{\mu}_{i|i-1} = \hat{\mu}_{i-1}, \qquad \hat{\sigma}^2_{i|i-1} = \hat{\sigma}^2_{i-1}, \tag{10}$$

$$\mathbb{D}(\mu_i^* - \hat{\mu}_{i|i-1}) \approx D_i^\mu, \qquad \mathbb{D}(\sigma_i^{*2} - \hat{\sigma}^2_{i|i-1}) \approx D_i^\sigma, \tag{11}$$

where D_i^μ, D_i^σ are recursively smoothed statistics with momentum α:

$$D_i^\mu \leftarrow (1-\alpha)D_{i-1}^\mu + \alpha(\mu_i - \hat{\mu}_{i-1})^2, \qquad D_i^\sigma \leftarrow (1-\alpha)D_{i-1}^\sigma + \alpha(\sigma_i^2 - \hat{\sigma}^2_{i-1})^2. \tag{12}$$

Combining Eqs. 5–12, we obtain the confidence-adaptive update scheme. When distributional shifts are rapid, D_i^μ and D_i^σ grow large, increasing K_i^μ and K_i^σ and accelerating adaptation. Conversely, when statistics are stable, these terms shrink, lowering K_i^μ and K_i^σ and reducing noise from small mini-batches.

4.3 Re-calibration Mechanism of BN Statistics (Re-BN)

While the confidence-adaptive update provides online estimates of BN statistics during training, these estimates may still drift from the true population values due to stochastic mini-batch noise. The most accurate approach would be to recompute exact statistics by forward-propagating the entire dataset after each update (Wu & Johnson, 2021). However, this is computationally infeasible in RL, as it would require processing millions of samples at every step.

A more practical alternative is to periodically re-calibrate BN statistics using larger aggregated batches. Specifically, at fixed intervals T_{cal}, we draw M calibration batches $\{\mathcal{B}_1, \ldots, \mathcal{B}_M\}$ from the replay buffer. For each batch $\mathcal{B}_j$, we compute its mean μ_j and variance σ_j^2. The recalibrated BN statistics are then given by:

$$\hat{\mu}_i = \frac{1}{M}\sum_{j=1}^{M}\mu_j, \qquad \hat{\sigma}_i^2 = \frac{1}{M}\sum_{j=1}^{M}(\sigma_j^2 + \mu_j^2) - \hat{\mu}_i^2. \tag{13}$$

This recalibration requires additional forward passes, but the extra overhead is upper bounded by $\frac{M}{T_{\text{cal}}}$ times the total training cost. Since we set $T_{\text{cal}} \gg M$, the computational overhead remains negligible, while significantly improving the accuracy of BN statistics.

4.4 Integrating with RL

The proposed Confidence-adaptive and Re-calibration Batch Normalization (CaRe-BN) integrates two complementary mechanisms: the confidence-adaptive update in Section 4.2, which provides an online estimation of batch normalization (BN) statistics, and the re-calibration procedure in Section 4.3, which corrects accumulated bias. The overall integration within an online RL framework is outlined in Algorithm 1.

Algorithm 1 General RL Algorithm with CaRe-BN

1: Initialize the agent networks and the replay buffer.
2: **for** each iteration **do**
3: Select an action and store the transition (**inference BN statistics**).
4: Update the agent by sampling a minibatch of N transitions (**mini-batch BN statistics**).
5: Update the moving BN statistics as:

$$D_i^{\mu} \leftarrow (1-\alpha)D_{i-1}^{\mu} + \alpha(\mu_i - \hat{\mu}_{i-1})^2, \qquad D_i^{\sigma} \leftarrow (1-\alpha)D_{i-1}^{\sigma} + \alpha(\sigma_i^2 - \hat{\sigma}_{i-1}^2)^2,$$

$$\hat{\mu}_i = \frac{D_i^{\mu}\cdot\mu_i + \frac{\sigma_i^2}{N}\cdot\hat{\mu}_{i-1}}{D_i^{\mu} + \frac{\sigma_i^2}{N}}, \qquad \hat{\sigma}_i^2 = \frac{D_i^{\sigma}\cdot\sigma_i^2 + \frac{2\sigma_i^4}{N-1}\cdot\hat{\sigma}_{i-1}^2}{D_i^{\sigma} + \frac{2\sigma_i^4}{N-1}}.$$

6: **if** Re-calibration **then**
7: Sample M minibatches of N transitions each and update BN statistics using Eq. (13).
8: **end if**
9: **end for**

It is important to note that the inference procedure of CaRe-BN remains identical to that of conventional BN. Consequently, the CaRe-BN layer is seamlessly fused into synaptic weights, introducing no additional inference overhead during deployment.

5 Experiments

5.1 Experiment Setup

We evaluate our CaRe-BN on five standard continuous control benchmarks from the MuJoCo suite (Todorov et al., 2012; Todorov, 2014b) within the OpenAI Gymnasium (Brockman, 2016; Towers et al., 2024), including InvertedDoublePendulum (IDP) (Todorov, 2014a), Ant (Schulman et al., 2015), HalfCheetah (Wawrzyński, 2009), Hopper (Erez et al., 2012), and Walker2d. All environments use default settings, and performance is evaluated by averaging the rewards over 10 trials.

To assess the effectiveness and adaptability of CaRe-BN, we conduct experiments with different spiking neuron models and RL algorithms. For spiking neurons, we test the Leaky Integrate-and-Fire (LIF) (Gerstner & Kistler, 2002) and Current-based LIF (CLIF) (Tang et al., 2021), with the dynamics detailed in Appendix. For RL algorithms, we employ Deep Deterministic Policy Gradient (DDPG) (Lillicrap, 2015) and Twin Delayed DDPG (TD3) (Fujimoto et al., 2018). All SNNs are simulated with a time step of 5, and additional training details are provided in Appendix.

For a fair comparison, we maintain consistent hyperparameters across all models and algorithms, with full settings provided in Appendix. Each algorithm is trained using 5 random seeds, and we report the averaged results.

5.2 More Precise BN Statistics Lead to Better Exploration

A key aspect of online RL is that the quality of exploration significantly influences subsequent policy updates. Figure 3 compares the exploration performance of standard BN with our proposed CaRe-BN. Throughout the training process, CaRe-BN consistently achieves higher exploration returns.

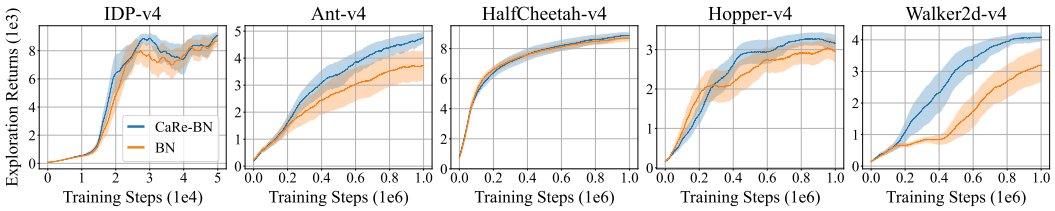

Figure 3: Exploration performance of BN and CaRe-BN with CLIF neurons and the TD3 algorithm across five MuJoCo tasks. Shaded areas represent half a standard deviation across five random seeds. Curves are uniformly smoothed for visual clarity.

Since CaRe-BN does not directly modify the gradient update process, the observed improvement in exploration performance is solely due to its more precise estimation of BN statistics. This leads to better exploration policies, which in turn generate higher-quality trajectories for updating the agent. As a result, CaRe-BN forms a positive feedback loop: improved statistics $\rightarrow$ better exploration $\rightarrow$ higher-quality experiences $\rightarrow$ better policy.

5.3 Adaptability of CaRe-BN

To evaluate the adaptability of CaRe-BN, we test it across different RL algorithms (i.e., DDPG (Lillicrap, 2015) and TD3 (Fujimoto et al., 2018)) and spiking neuron models (i.e., LIF and CLIF (Tang et al., 2021)).

Better final return. Figure 4 shows the learning curves for SNN models with and without CaRe-BN. In most cases, CaRe-BN consistently outperforms standard SNNs, converging faster and achieving higher final returns. These improvements are robust across different spiking neurons and RL algorithms, confirming that CaRe-BN enhances performance in diverse settings.

Lower variance. Figure 5 (a) and (b) display the relative variance of the final policy. Compared to standard SNNs, CaRe-BN significantly reduces the variance of SNN-RL training, and even achieves lower variance than ANN baselines (i.e., 17.71% for DDPG and 21.24% for TD3). This indicates that CaRe-BN not only enhances performance but also improves the stability and reproducibility of SNN-RL.

5.4 Exceeding SOTA

To further validate the effectiveness of CaRe-BN, we compare it with existing state-of-the-art (SOTA) SNN-RL methods and various batch normalization strategies for SNNs. The evaluation is conducted using the TD3 algorithm (Fujimoto et al., 2018) (a strong SOTA baseline for continuous control) and the CLIF neuron model (Tang et al., 2021) (the most commonly used neuron type in recent SNN-RL studies). The ANN-SNN conversion baseline follows the SOTA method proposed in Bu et al. (2025). For direct-trained SNNs, we include pop-SAN (Tang et al., 2021), MDC-SAN (Zhang et al., 2022), and ILC-SAN (Chen et al., 2024a). Additionally, we test several BN algorithms for SNNs, including tdBN (Zheng et al., 2021), BNTT (Kim & Panda, 2021), TEBN (Duan et al., 2022), and TABN (Jiang et al., 2024). The performance is summarized in Table 1, where the average

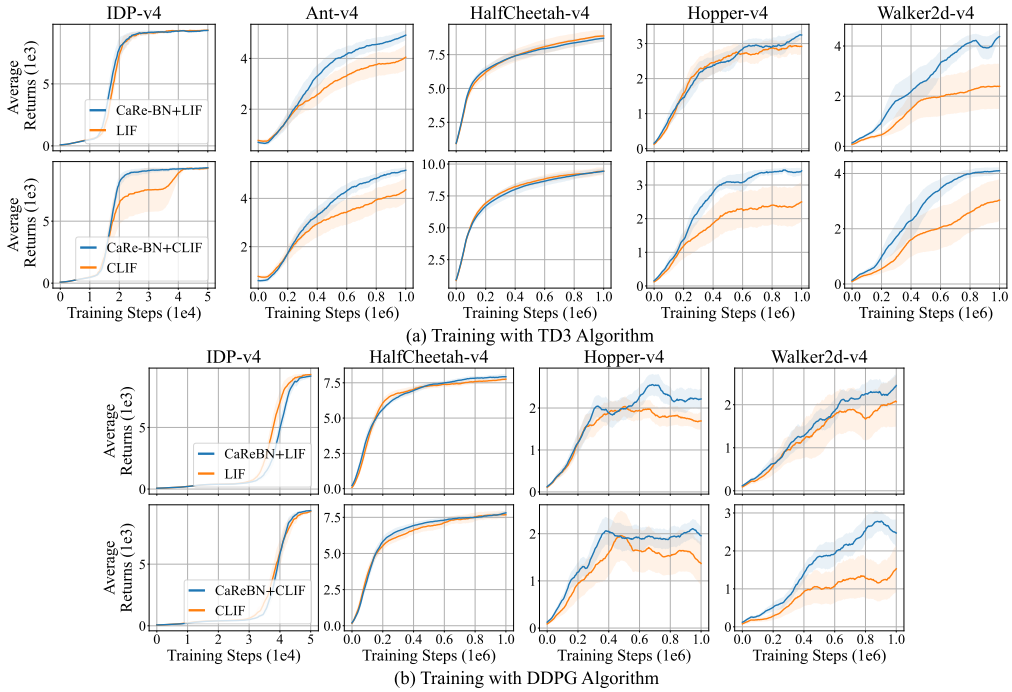

Figure 4: Learning curves of SNN-based agents trained with TD3 (top) and DDPG (bottom). Since the DDPG algorithm (in both ANN and SNN) diverges in the Ant-v4 environment, these curves are not shown. Shaded areas represent half a standard deviation across five random seeds. Curves are uniformly smoothed for visual clarity.

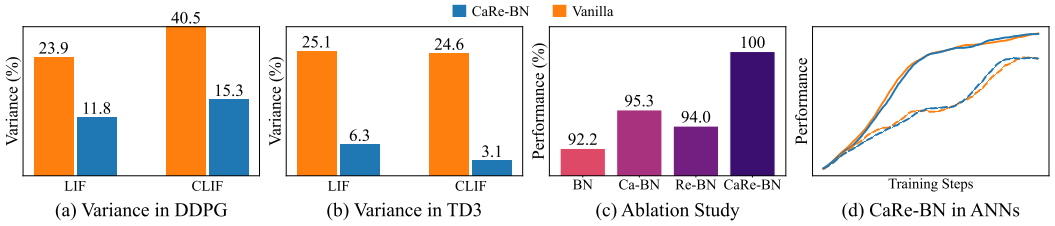

Figure 5: (a), (b) Relative variance percentage of final policy returns, computed by averaging the standard deviation ratio across five random seeds, for all environments. (c) Normalized maximum performance across all environments for the ablation study. (d) Normalized learning curves across all environments for ANNs implementing CaRe-BN. The dashed lines represent DDPG and the solid lines represent TD3. Performance and training steps are normalized linearly. Curves are uniformly smoothed for visual clarity.

performance gain (APG) is defined as:

$$APG = \left(\frac{1}{|\text{envs}|} \sum_{\text{env} \in \text{envs}} \frac{\text{performance}(\text{env})}{\text{baseline}(\text{env})} - 1 \right) \cdot 100\%, \tag{14}$$

where $|\text{envs}|$ denotes the total number of environments, and $\text{performance}(\text{env})$ and $\text{baseline}(\text{env})$ represent the performance of the evaluated algorithm and the ANN baseline in each environment, respectively.

Compared with other SNN-RL methods: CaRe-BN significantly outperforms previous SNN-RL approaches, demonstrating that normalization plays a more crucial role than architectural modifications in improving SNN-RL performance.

Compared with other BN methods: Compared to existing SNN-specific BN variants, CaRe-BN performs superior, establishing a new state-of-the-art normalization strategy for SNN-RL.

Compared with ANNs: Notably, CaRe-BN outperforms the ANN baseline by 5.9% on average. This highlights that with proper normalization, SNNs can not only match but exceed the performance of traditional ANN-based RL agents, while retaining their energy-efficient advantages.

Table 1: Max average returns over 5 random seeds with CLIF spiking neurons, and the average performance gain (APG) against ANN baseline, where $\pm$ denotes one standard deviation.

Method	IDP-v4	Ant-v4	HalfCheetah-v4	Hopper-v4	Walker2d-v4	APG
ANN (TD3)	7503 ± 3713	4770 ± 1014	10857 ± 475	3410 ± 164	4340 ± 383	0.00%
ANN-SNN	3859 ± 4440	3550 ± 963	8703 ± 658	3098 ± 281	4235 ± 354	-21.11%
pop-SAN	9351 ± 1	4590 ± 1006	9594 ± 689	2772 ± 1263	3307 ± 1514	-6.66%
MDC-SAN	9350 ± 1	4800 ± 994	9147 ± 231	3446 ± 131	3964 ± 1353	0.37%
ILC-SAN	9352 ± 1	5584 ± 272	9222 ± 615	3403 ± 148	4200 ± 717	4.64%
tdBN	9346 ± 2	4403 ± 1134	9402 ± 527	3592 ± 46	3464 ± 970	-2.28%
BNTT	9347 ± 1	4379 ± 941	9466 ± 659	3524 ± 161	3689 ± 1247	-1.62%
TEBN	9349 ± 1	4408 ± 1156	9452 ± 539	3472 ± 135	4235 ± 381	0.69%
TABN	9348 ± 2	4382 ± 753	9784 ± 169	3585 ± 83	4537 ± 398	3.25%
CaRe-BN	9348 ± 2	5373 ± 159	9563 ± 442	3586 ± 49	4296 ± 268	$\mathbf{5.90}\%$

5.5 Ablation Studies

We conduct ablation studies by separately evaluating the effects of the Confidence-adaptive update (Ca-BN) and the Re-calibration mechanism (Re-BN), as shown in Figure 5 (c). The results demonstrate that both the adaptive estimation and recalibration mechanisms are beneficial on their own. However, their combination provides the most significant improvement. Specifically, Ca-BN addresses the mismatch between training and inference statistics, while Re-BN corrects accumulated errors, further stabilizing training. By integrating both components, CaRe-BN achieves more precise and consistent normalization, leading to superior overall performance.

5.6 SNN-friendly design

Dispite the stunning improvement in SNNs, we also evaluate CaRe-BN on standard ANNs trained with TD3 and DDPG, as shown in Figure 5 (d). The results indicate that ANNs with CaRe-BN perform similarly to their baseline counterparts without CaRe-BN. This outcome is expected for the following reasons: ***(i)*** Shallow ANNs can already train stably and effectively without normalization[1], so adding CaRe-BN does not provide significant improvements. ***(ii)*** While CaRe-BN provides more precise estimates of BN statistics, this does not negatively impact the RL training process. These results further underscore that the improvements observed are not due to a stronger RL mechanism, but rather to the SNN-specific normalization strategies.

6 Conclusion

In this work, we introduced CaRe-BN, the first batch normalization method specifically designed for SNNs in RL. By addressing the instability of conventional BN in online RL, CaRe-BN enables SNNs to outperform their ANN counterparts in continuous control tasks. Importantly, CaRe-BN is lightweight and easy to integrate, making it a seamless drop-in replacement for existing SNN-RL pipelines without introducing additional computational overhead.

Beyond its technical contributions, CaRe-BN brings SNN-RL one step closer to practical deployment. By stabilizing training and improving exploration, it unlocks the potential of SNNs to act as both energy-efficient and high-performance agents in real-world continuous control applications. We believe this work underscores the importance of normalization strategies tailored to the unique dynamics of SNNs and opens new avenues for bridging the gap between neuromorphic learning and reinforcement learning at scale.

[1] In RL, networks typically consist of two hidden layers with 256 neurons

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A Ethics Statement

Our submission follows the ICLR Code of Ethics. We do not identify any specific ethical concerns in this work.

B Reproducibility Statement

Source code are provided in the supplementary materials. We also provide our full implementation and experimental configurations in the Appendix. All experiments were conducted on a single NVIDIA RTX 4090 GPU, but the code can also be executed on CPU-only devices, albeit with longer training times. These materials ensure that the reported results can be reproduced and verified by the community.

C Use of Large Language Models

Large Language Models (LLMs) were used solely for polishing the presentation of this paper, such as correcting typos, improving grammar. All ideas, derivations, algorithm design, and experiments were conceived and implemented independently **without** reliance on LLMs.

D Appendix

D.1 Spiking Actor Network Architecture

The Spiking Actor Network (SAN) consists of a population encoder with Gaussian receptive fields, a multi-layer SNN with a population output, and a decoder with non-firing neurons.

D.1.1 Forward Propagation of the SAN

In the state encoder, each input dimension is represented by N_{in} soft-reset IF neurons with Gaussian receptive fields. These fields have trainable parameters μ and σ. The neurons receive stimulation A_E at every time step and output spikes S^{in} according to:

$$A_E = \exp\left[-\frac{1}{2}\frac{(s-\mu)^2}{\sigma^2}\right] \tag{15}$$

$$\begin{aligned} V_t^{in} &= V_{t-1}^{in} - S_{t-1}^{in} + A_E, \\ S_t^{in} &= \Theta(V_t^{in} - V_E), \end{aligned} \tag{16}$$

where V_E is the threshold for the encoding populations.

The final layer of the SNN consists of N_{out} neurons, corresponding to each action dimension. The decoder layer consists of non-spiking integrate-and-fire neurons connected to the last layer of the SNN:

$$V_t^{out} = V_{t-1}^{out} + W^{out} \cdot S_t^L + b^{out}, \tag{17}$$

where W^{out} and b^{out} are the weights and biases, respectively. The final output action is determined by the membrane potential at the last time step, $a = V_T^{out}$. A detailed description of the forward propagation in the spiking actor network is provided in Algorithm 2.

D.1.2 Backpropagation of the SAN

The SAN parameters are optimized using gradients with respect to the output action $a = V_T^{out}$, given $\frac{\partial L}{\partial a}$.

For the decoder:

$$\begin{aligned} \frac{\partial L}{\partial W^{out}} &= \frac{\partial L}{\partial a} \cdot \frac{\partial V_T^{out}}{\partial W^{out}}, \\ \frac{\partial L}{\partial b^{out}} &= \frac{\partial L}{\partial a} \cdot \frac{\partial V_T^{out}}{\partial b^{out}}. \end{aligned} \tag{18}$$

Algorithm 2 Forward propagation of the Spiking Actor Network (SAN)

Input: M_s-dimensional observation s
Compute input population stimulation:

$$A_E = \exp\left[-\frac{1}{2}\frac{(s-\mu)^2}{\sigma^2}\right]$$

for $t = 1, \ldots, T$ **do**
  Compute encoder membrane potential and spikes:

$$V_t^{in} = V_{t-1}^{in} - S_{t-1}^{in} + A_E, \quad S_t^{in} = \Theta(V_t^{in} - V_E)$$

  for $l = 1, \ldots, L$ **do**
    Update neurons in layer l at timestep t
  end for
  Update decoder membrane potential:

$$V_t^{out} = V_{t-1}^{out} + W^{out} \cdot S_t^L + b^{out}$$

end for
Output: M_a-dimensional action $a = V_T^{out}$

The main SNN is trained using spatio-temporal backpropagation (STBP) (Wu et al., 2018), with the rectangular surrogate gradient function defined as:

$$\Theta'(x) = \begin{cases} \frac{1}{2\omega}, & -\omega \le x \le \omega, \\ 0, & \text{otherwise}, \end{cases} \tag{19}$$

where ω denotes the window size.

Next, we derive the gradient of the encoder stimulation A_E, as shown in Eq. 20. For simplicity, the term $\frac{\partial S_t^{in}}{\partial A_E}$ is manually set to 1, which is a common surrogate assumption to simplify gradient computation:

$$\frac{\partial L}{\partial A_E} = \sum_{t=1}^{T} \frac{\partial L}{\partial S_t^{in}} \cdot \frac{\partial S_t^{in}}{\partial A_E} = \sum_{t=1}^{T} \frac{\partial L}{\partial S_t^{in}}. \tag{20}$$

Finally, the trainable parameters μ and σ of the encoder can be updated as:

$$\begin{aligned} \frac{\partial L}{\partial \mu} &= \frac{\partial L}{\partial A_E} \cdot \frac{\partial A_E}{\partial \mu} = \frac{\partial L}{\partial A_E} \cdot \frac{s-\mu}{\sigma^2} A_E, \\ \frac{\partial L}{\partial \sigma} &= \frac{\partial L}{\partial A_E} \cdot \frac{\partial A_E}{\partial \sigma} = \frac{\partial L}{\partial A_E} \cdot \frac{(s-\mu)^2}{\sigma^3} A_E. \end{aligned} \tag{21}$$

D.2 Spiking Neuron Models

Section 3.1 introduced the LIF neuron model. Here, we provide the detailed dynamics of the two spiking neuron models used in our experiments.

D.2.1 LIF Neuron Model

The dynamics of the LIF neuron are defined in Eq. 1, where the input current is computed as:

$$C_t^l = W^l S_t^{l-1} + b^l, \tag{22}$$

where W and b denote the synaptic weights and biases, respectively.

D.2.2 Current-Based LIF (CLIF) Neuron Model

In the current-based LIF (CLIF) neuron proposed in Tang et al. (2021), the input current in Eq. 22 is modified as:

$$C_t^l = \lambda_c I_{t-1}^l + W^l S_t^{l-1} + b^l, \tag{23}$$

where λ_c is the current leakage parameter. All other dynamics of CLIF neurons are identical to those of standard LIF neurons.

D.3 Experiment Details

D.3.1 Compute Resources

All experiments were conducted on an RTX 4090 GPU.

D.3.2 Spiking Neuron Parameters

The parameters for the LIF and CLIF neurons are listed in Table 2. These are the same as those used in Tang et al. (2021), except that the LIF neuron does not include a current leakage parameter.

Table 2: Parameters of LIF and CLIF (Tang et al., 2021) neurons

Parameter	LIF	CLIF (Tang et al., 2021)
Membrane leakage parameter λ	0.75	0.75
Threshold voltage V_{th}	0.5	0.5
Reset voltage V_{reset}	0	0
Current leakage parameter α	-	0.5

D.3.3 Specific Parameters for CaRe-BN

Table 3 lists the hyperparameters of CaRe-BN. The recalibration frequency T_{re} is set equal to the evaluation frequency used in the RL algorithms. All hyperparameters are kept consistent across different spiking neuron models and RL algorithms.

Table 3: Hyper-parameters of the CaRe-BN

Parameter	Value
Momentum α	0.8
Recalibration frequency T_{re}	5000
Recalibration batchs M	100

D.3.4 Spiking Actor Network Parameters

All hyper-parameters of the spiking actor network are listed in Table 4. These settings are consistent with those used in a wide range of previous studies (Tang et al., 2021; Zhang et al., 2022; Chen et al., 2024a).

Table 4: Hyper-parameters of the spiking actor network

Parameter	Value
Encoder population per dimension N_{in}	10
Encoder threshold V_E	0.999
Network hidden units	$(256, 256)$
Decoder population per dimension N_{out}	10
Surrogate gradient window size ω	0.5

D.3.5 RL Algorithm Parameters

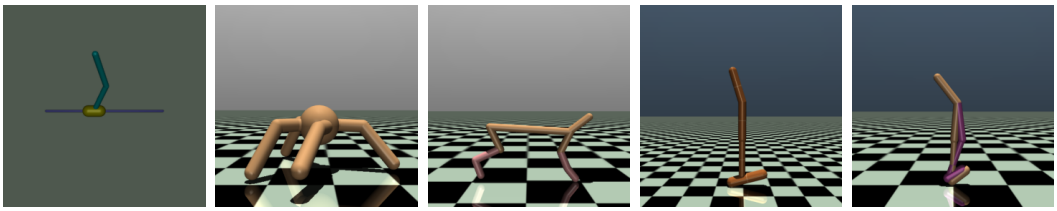
The experiments are conducted using the DDPG (Lillicrap, 2015) and TD3 (Fujimoto et al., 2018) algorithms, with their respective hyperparameters listed in Tables 5 and 6.

Table 5: Hyper-parameters of the implemented DDPG algorithm (Lillicrap, 2015)

Parameter	Value
Actor learning rate	$1 \cdot 10^{-4}$
Actor regularization	None
Critic learning rate	$1 \cdot 10^{-3}$
Critic regularization	weight decay =0.01
Critic architecture	$(400, 300)$
Critic activation	Relu
Optimizer	Adam
Target update rate τ	$5 \cdot 10^{-3}$
Batch size N	256
Discount factor γ	0.99
Iterations per time step	1.0
Reward scaling	1.0
Gradient clipping	None
Replay buffer size	10^6
Exploration niose $\mathcal{N}(0, \sigma)$	$\mathcal{N}(0, 0.2)$

Table 6: Hyper-parameters of the implemented TD3 algorithm (Fujimoto et al., 2018)

Parameter	Value
Actor learning rate	$3 \cdot 10^{-4}$
Actor regularization	None
Critic learning rate	$3 \cdot 10^{-4}$
Critic regularization	None
Critic architecture	$(256, 256)$
Critic activation	Relu
Optimizer	Adam
Target update rate τ	$5 \cdot 10^{-3}$
Batch size N	256
Discount factor γ	0.99
Iterations per time step	1.0
Reward scaling	1.0
Gradient clipping	None
Replay buffer size	10^6
Exploration niose $\mathcal{N}(0, \sigma)$	$\mathcal{N}(0, 0.1)$
Actor update interval d	2
Target policy noise $\mathcal{N}(0, \tilde{\sigma})$	$\mathcal{N}(0, 0.2)$
Target policy noise clip c	0.5



(a) IDP-v4 (b) Ant-v4 (c) HalfCheetah-v4 (d) Hopper-v4 (e) Walker2d-v4

Figure 6: Several continuous control tasks of the MuJoCo environments on OpenAI Gymnasium. (a) InvertedDoublePendulum-v4, (b) Ant-v4, (c) HalfCheetah-v4, (d) Hopper-v4, (e) Walker2d-v4.

D.3.6 EXPERIMENT ENVIRONMENTS

Figure 6 illustrates various MuJoCo environments (Todorov et al., 2012; Todorov, 2014b) from the OpenAI Gymnasium benchmarks (Brockman, 2016; Towers et al., 2024), including Inverted-DoublePendulum (IDP) (Todorov, 2014a), Ant (Schulman et al., 2015), HalfCheetah (Wawrzyński, 2009), Hopper (Erez et al., 2012), and Walker. All environments used the default configurations without modification.

Note that the state vectors, which can range from $-\infty$ to ∞, are normalized to $(-1, 1)$ using a tanh function. Similarly, since the actions have minimum and maximum limits, the outputs of the actor network are first normalized to $(-1, 1)$ via a tanh function and then linearly scaled to the corresponding $(\text{Min action}, \text{Max action})$ range.

D.4 ADDITIONAL EXPERIMENTAL RESULTS

D.4.1 ADDITIONAL RESULTS ON ADAPTABILITY

In the main text, we demonstrated that CaRe-BN improves performance across various spiking neuron models and RL algorithms. Additionally, Tables 7, 8, 9, and 10 report the maximum average returns and the average performance gains of CaRe-BN compared to vanilla SNNs across different spiking neurons and RL algorithms.

Table 7: Max average returns over 5 random seeds in DDPG with LIF neurons.

Method	IDP	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	9352 ± 1	7954 ± 356	3035 ± 127	2931 ± 1395	$\mathbf{0.00}\%$
CaRe-BN	9351 ± 1	8199 ± 305	3512 ± 79	3347 ± 321	$\mathbf{8.24}\%$

Table 8: Max average returns over 5 random seeds in DDPG with CLIF neurons.

Method	IDP	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	9352 ± 2	8205 ± 376	2566 ± 1270	2224 ± 1607	$\mathbf{0.00}\%$
CaRe-BN	9352 ± 0	7972 ± 245	3247 ± 100	3709 ± 321	$\mathbf{22.62}\%$

Table 9: Max average returns over 5 random seeds in TD3 with LIF neurons.

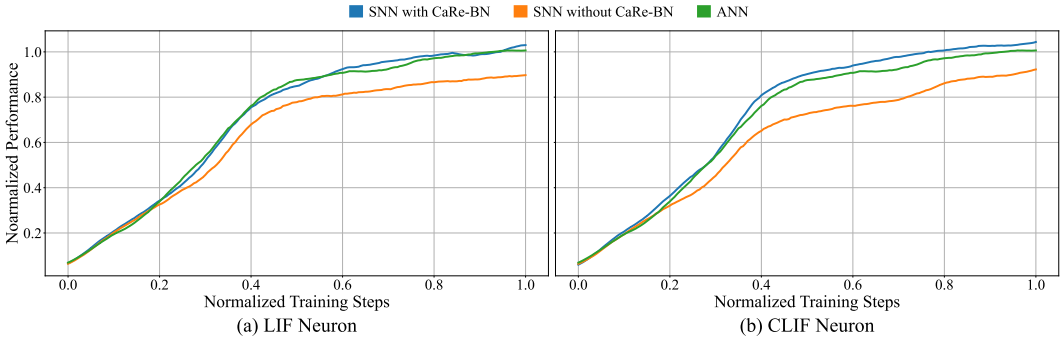
Method	IDP	Ant	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	9347 ± 1	4243 ± 949	9073 ± 946	3507 ± 85	2807 ± 1834	$\mathbf{0.00}\%$
CaRe-BN	9346 ± 1	5083 ± 356	8813 ± 533	3489 ± 118	4556 ± 497	$\mathbf{15.74}\%$

D.4.2 ADDITIONAL COMPARISON WITH ANNS

Fig.7 shows the normalized learning curves of our CaRe-BN within different spiking neurons.

Table 10: Max average returns over 5 random seeds in TD3 with CLIF neurons.

Method	IDP	Ant	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	9351 ± 1	4590 ± 1006	9594 ± 689	2772 ± 1263	3307 ± 1514	$\mathbf{0.00}\%$
CaRe-BN	9348 ± 2	5373 ± 159	9563 ± 442	3586 ± 49	4296 ± 268	$\mathbf{15.20}\%$



(a) LIF Neuron (b) CLIF Neuron

Figure 7: Normalized learning curves across all environments of the CaRe-BN with different spiking neurons across all environments. The performance and training steps are normalized linearly based on ANN performance. Curves are uniformly smoothed for visual clarity.

D.4.3 Additional comparison with other SNN-BN mechanisms

Tab. 11, shows the performance of different BN variants and CaRe-BN with the LIF neuron model in TD3 algorithm.

Table 11: Max average returns over 5 random seeds with LIF neuron, and the average performance gain (APG) against ANN baseline, where $\pm$ denotes one standard deviation.

Method	IDP-v4	Ant-v4	HalfCheetah-v4	Hopper-v4	Walker2d-v4	APG
ANN (TD3)	7503 ± 3713	4770 ± 1014	10857 ± 475	3410 ± 164	4340 ± 383	0.00%
Vanilla LIF	9347 ± 1	4243 ± 949	9073 ± 946	3507 ± 85	2807 ± 1834	-7.08%
tdBN	9346 ± 1	4876 ± 577	8845 ± 526	3601 ± 29	4098 ± 408	1.65%
BNTT	9348 ± 1	5244 ± 321	9339 ± 874	3593 ± 62	3480 ± 1450	1.22%
TEBN	9347 ± 1	4408 ± 1156	9452 ± 539	3472 ± 135	4235 ± 381	0.69%
TABN	9347 ± 1	4431 ± 1353	9173 ± 595	3474 ± 183	3818 ± 1133	-1.64%
CaRe-BN	9346 ± 1	5083 ± 356	8813 ± 533	3489 ± 118	4556 ± 497	3.92%

D.4.4 Additional results in ANN

We shows the normalized learning curves of the CaRe-BN with ANN in Fig.5 (d). Here, we show the detailed learning curves and maximum average returns of 5 environments in Fig.8, Fig.9, Tab.12 and Tab. 13, respectively.

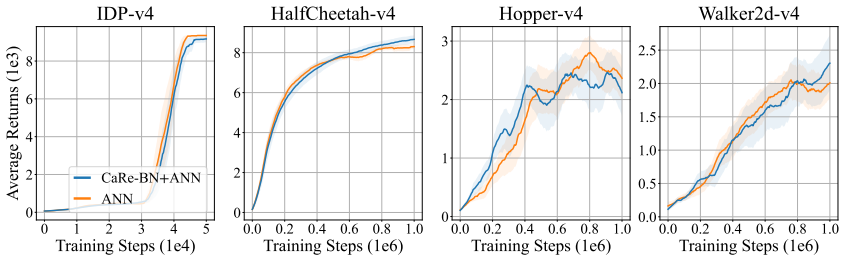


Figure 8: Learning curves of utilizing CaRe-BN in ANN with DDPG algorithm. The shaded region represents half a standard deviation over 5 different seeds. Curves are uniformly smoothed for visual clarity.

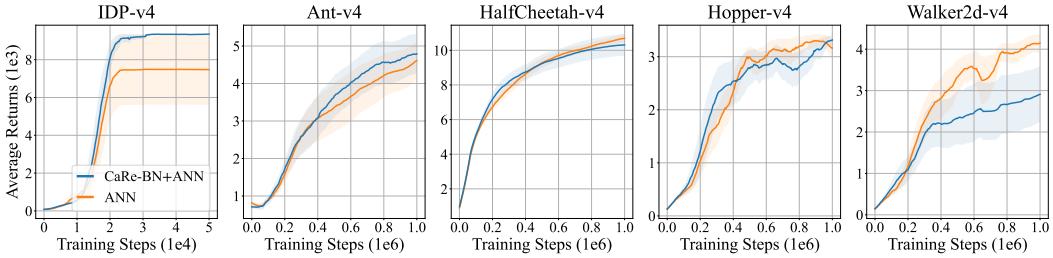


Figure 9: Learning curves of utilizing CaRe-BN in ANN with TD3 algorithm. The shaded region represents half a standard deviation over 5 different seeds. Curves are uniformly smoothed for visual clarity.

Table 12: Max average returns over 5 random seeds in DDPG with ANN.

Method	IDP	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	9357 ± 4	8604 ± 241	3486 ± 162	3385 ± 408	$\mathbf{0.00}\%$
CaRe-BN	9360 ± 0	8887 ± 408	3475 ± 135	3328 ± 882	$\mathbf{0.33}\%$

Table 13: Max average returns over 5 random seeds in TD3 with ANN.

Method	IDP	Ant	HalfCheetah	Hopper	Walker2d	APG
Vanilla SNN	7503 ± 3713	4770 ± 1014	10857 ± 475	3410 ± 164	4340 ± 383	$\mathbf{0.00}\%$
CaRe-BN	9360 ± 0	5014 ± 1122	10458 ± 1271	3436 ± 114	3021 ± 1360	$-\mathbf{0.69}\%$