

Q-VGM: Q-Guided Value-Gradient Matching for Offline-to-Online RL of Flow-Matching VLA Policies

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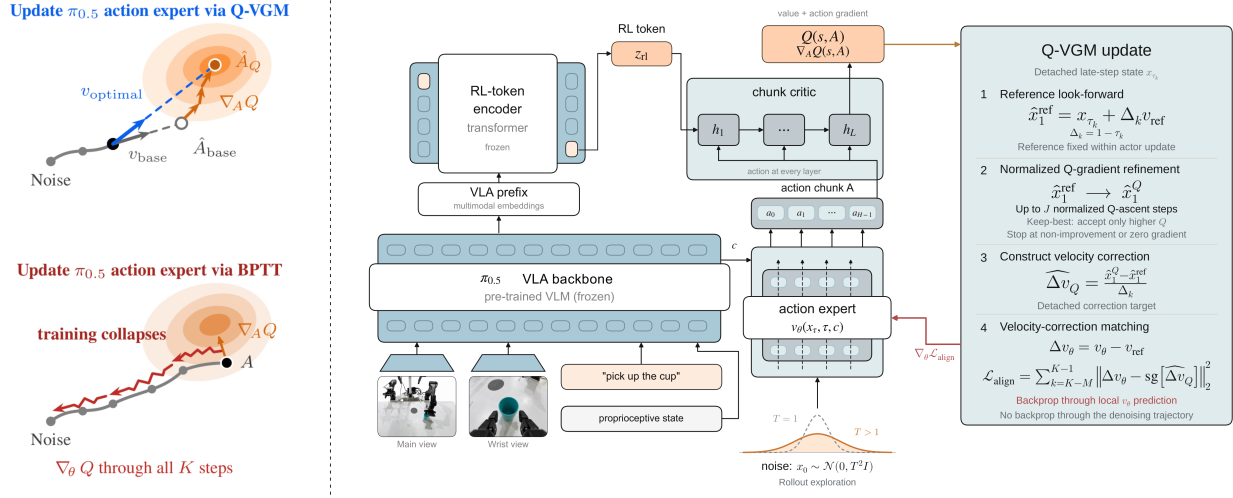


Fig. 1. **Q-VGM at a glance.** *Left:* Q-VGM moves the action expert along the critic gradient $\nabla_A Q$ through a local velocity target at a late denoising step, whereas backpropagating $\nabla_\theta Q$ through all K denoising steps (BPTT) collapses training. *Right:* a frozen $\pi_{0.5}$ backbone provides an RL token z_{rl} to an action-sensitive chunk critic $Q(s, A)$; the reference look-forward $\hat{x}_1^{\text{ref}}$ is refined by up to J normalized Q -gradient ascent steps, converted to a velocity target $v_{\text{ref}} + \hat{\Delta} v_Q$, and matched by the action expert v_θ with gradients flowing only through v_θ .

Abstract—We propose *Q-Guided Value-Gradient Matching* (Q-VGM), an offline-to-online RL method for fine-tuning flow-matching vision-language-action policies with a learned critic. Directly applying critic gradients to flow policies requires backpropagation through the multi-step denoising process (BPTT), which is costly and unstable at VLA scale. Motivated by an optimal-control view of denoising, we derive a local approximation connecting clean-action value gradients to local velocity corrections at late denoising steps. Q-VGM uses this connection to construct critic-guided targets for fine-tuning the pretrained action expert through velocity matching. Gradients pass only through local velocity predictions, avoiding backpropagation through the denoising trajectory. An action-sensitive chunk critic is trained with IQL offline and TD learning online. On LIBERO, Q-VGM improves the few-shot-SFT four-suite average from 84.6% to 90.7% offline using 150 policy rollouts per suite, and reaches 98.4% after online training. Compared with on-policy RL, Q-VGM achieves $5.3\times$ higher sample efficiency on average across four LIBERO suites, measured by the episode budget for 95% rollout success rate. On three real-world bimanual tasks, offline Q-VGM improves average success from 66.7% to 98.3%.

I. INTRODUCTION

Vision-language-action (VLA) models bridge high-level multimodal reasoning and low-level continuous control [1]–[5]. Flow-matching action experts have become their dominant backbone: by transporting noise to action chunks through iterative denoising, they capture the multimodal

action distributions required for dexterous, long-horizon manipulation [4]–[7].

The prevailing post-training recipe for VLA models is supervised fine-tuning (SFT) on expert demonstrations, which inherits the fundamental limitation of imitation learning: performance is bounded by the quality and coverage of the demonstrations, while the abundant failed and suboptimal rollouts a policy produces carry no learning signal. Reinforcement learning (RL) removes this bound by directly optimizing task success, allowing a policy to learn from its own experience and exceed its demonstrator.

Realizing this potential for flow-matching VLAs is difficult. On-policy methods such as PPO and GRPO require fresh rollouts from the current policy for each optimization round and discard the collected experience after that round [8]–[11]. Their sample efficiency is therefore inherently limited, which is tolerable in simulation but becomes the dominant cost on real robots, where every rollout episode is expensive. Off-policy value-based RL avoids this inefficiency: all experience is stored in a replay buffer and repeatedly reused to train a Q -function [12]. The same machinery applies when the buffer is fixed in advance, so off-policy training naturally spans both an offline phase on previously collected data and an online phase on freshly gathered experience [13]. To improve the policy, classical

off-policy actor–critic methods such as TD3 and SAC adjust the policy parameters to ascend the critic along its action gradient $\nabla_A Q(s, A)$ [12], [14]. For a flow-matching policy, however, this update requires backpropagating through the entire denoising chain (backpropagation through time, BPTT) [15]. The resulting gradient contains products of denoising-step Jacobians, which can amplify or attenuate the critic signal and destabilize policy optimization [16]. In our VLA fine-tuning experiments, we observe exploding actor gradients and training collapse under this update (Fig. 2).

BPTT-free policy extraction has also been explored for generative policies [16], [17]. In our setting, the critic evaluates clean action chunks, whereas the pretrained VLA generates actions through iterative denoising. We therefore focus on converting clean-action value gradients into local velocity supervision, without differentiating through the denoising trajectory.

To address this challenge, we propose *Q-Guided Value-Gradient Matching* (Q-VGM), an off-policy fine-tuning method for flow-matching VLA policies. Motivated by an optimal-control view of denoising, we start from the relation between optimal velocity corrections and denoising-time value gradients. We derive a late-step approximation that estimates these value gradients using clean-action Q -gradients at reference-policy look-forward endpoints. This connection motivates a velocity-matching objective for fine-tuning the pretrained action expert.

In practice, Q-VGM refines these endpoint estimates through normalized Q -gradient ascent with keep-best selection. The accepted endpoint displacements are converted into local velocity targets. With denoising states and targets detached, backpropagation is restricted to local velocity predictions rather than the denoising trajectory. An action-sensitive chunk critic is trained on compact latent states from the frozen VLA prefix, using IQL offline and standard TD learning online. At inference time, the policy samples with the fine-tuned velocity field alone, fully amortizing critic guidance into the action expert.

On LIBERO, offline Q-VGM lifts a few-shot-SFT $\pi_{0.5}$ policy from 84.6% to 90.7% average success across four suites with 150 rollout episodes per suite, and offline-to-online training reaches 98.4%, surpassing PPO fine-tuning (97.4%). Compared with on-policy RL, Q-VGM achieves $5.3\times$ higher sample efficiency on average across four LIBERO suites, measured by the episode budget for 95% rollout success rate with exploration noise. On three real bimanual manipulation tasks, offline Q-VGM raises the average success rate from 66.7% to 98.3%.

Our contributions are as follows.

(1) A BPTT-free velocity-matching method for VLA fine-tuning. Motivated by an optimal-control view of denoising, we derive a late-step approximation relating clean-action Q -gradients to velocity corrections. This connection motivates a local velocity-matching objective that directly fine-tunes the pretrained action expert without backpropagating through the denoising trajectory.

(2) An offline-to-online framework for flow-matching VLAs. We integrate critic-guided velocity matching with an action-sensitive chunk critic trained from a replay buffer. The framework uses the same actor objective across offline and online learning, with phase-specific critic backups and reference-policy updates.

(3) Empirical validation in simulation and on real robots. On LIBERO, we demonstrate offline policy improvement and more sample-efficient online fine-tuning than PPO. We further validate offline Q-VGM on three real-world bimanual manipulation tasks.

II. RELATED WORK

RL for VLA policies. PPO- and GRPO-style updates have been adapted to diffusion and flow policies through stochastic formulations or surrogate objectives [9]–[11], [18], [19]. A complementary line uses advantage-based supervised policy improvement [20]. For VLAs, RECAP [21] incorporates advantage-derived optimality indicators into supervised policy training. Alternatively, RL can optimize lightweight policies built on frozen VLA models. RLT [22] conditions a lightweight actor on compact VLA representations and reference actions, while PLD [23] learns residual policies and subsequently distills collected trajectories back into the VLA through SFT. In both cases, the RL updates operate on auxiliary policies rather than the pretrained action expert.

Value-guided optimization of diffusion and flow policies. Inference-time methods rank action candidates using value estimates, learned verifiers, or confidence scores [24]–[27]. QFQL [28] guides flow sampling at inference by adding critic gradients evaluated at intermediate noisy actions to the velocity field. These methods leave policy parameters unchanged.

At training time, Diffusion-QL [15] combines denoising behavior cloning with Q -maximization through backpropagation along the full denoising chain. EDP [29] reduces this cost through approximate action reconstruction, while DTQL [30] and FQL [31] optimize separate one-step actors with diffusion- and flow-based behavior regularization, respectively.

Q -score matching [16] instead provides denoising-time supervision without full-chain differentiation. Optimal-control and value-gradient formulations offer related perspectives on reward-guided fine-tuning [32]–[35]. QAM [17] uses adjoint matching for critic-guided policy extraction, while TRQAM [36] adds a path-space KL trust region. They study compact flow policies on state-based control benchmarks. Adjoint target construction still requires step-wise vector–Jacobian products through the reference velocity field, which can be computationally costly when scaling to large pretrained VLA action experts.

Offline-to-online reinforcement learning. Offline-to-online RL uses previously collected experience to initialize policies and value functions before further improvement through online interaction [13], [37]. Flow-based methods

such as FQL and QAM also study this setting on continuous-control benchmarks using compact policy networks rather than pretrained VLAs [17], [31].

III. PRELIMINARIES

A. Flow Matching for VLA Models

We use $\pi_{0.5}$, a flow-based vision-language-action model [4], [5]. Given a VLA conditioning context c , the action expert generates an action chunk $A = [a_0, a_1, \dots, a_{H-1}]$. We set $\tau = 0$ for Gaussian noise and $\tau = 1$ for the clean action chunk. Given noise $\epsilon \sim \mathcal{N}(0, I)$, the linear flow path is

$$x_\tau = (1 - \tau)\epsilon + \tau A, \quad \tau \in [0, 1].$$

The action expert predicts a velocity field $v_\theta(x_\tau, \tau, c)$ trained by conditional flow matching [6]. At inference time, sampling integrates this velocity over $0 = \tau_0 < \tau_1 < \dots < \tau_K = 1$, starting from $x_0 \sim \mathcal{N}(0, I)$.

We hold the conditioning context fixed and omit it below.

B. Value-Gradient Guidance for Flow Models

Let v_{ref} denote the velocity field of a reference policy. We consider policy improvement through a velocity correction Δv added to the reference denoising dynamics:

$$\dot{x}_\tau = v_{\text{ref}}(x_\tau, \tau) + \Delta v(x_\tau, \tau).$$

Let x_1^{ref} denote the endpoint reached from x_τ at time 1 when $\Delta v = 0$. Given a terminal score $r(x_1)$, we seek a correction that improves this score while penalizing deviations from v_{ref} . For $x_\tau = x$, define the denoising-time value function

$$V(x, \tau) = \sup_{\Delta v} \left[r(x_1) - \frac{\rho}{2} \int_\tau^1 \|\Delta v(x_u, u)\|_2^2 du \right], \quad (1)$$

where the trajectory follows the controlled dynamics and $\rho > 0$ controls the penalty strength. Thus, $V(x, \tau)$ is the best regularized terminal score reachable from the intermediate state x .

When V is continuously differentiable, it satisfies the Hamilton–Jacobi–Bellman (HJB) equation [38]:

$$0 = \partial_\tau V + \nabla_x V^\top v_{\text{ref}} + \max_{\Delta v} \left\{ \nabla_x V^\top \Delta v - \frac{\rho}{2} \|\Delta v\|_2^2 \right\}. \quad (2)$$

Maximizing the quadratic term with respect to Δv gives the optimal correction [35]:

$$\Delta v^*(x, \tau) = \frac{1}{\rho} \nabla_x V(x, \tau). \quad (3)$$

At the clean endpoint, the remaining control cost vanishes, giving $V(x_1, 1) = r(x_1)$ and $\nabla_x V(x_1, 1) = \nabla_{x_1} r(x_1)$.

IV. METHOD

We fine-tune a pretrained flow-matching VLA using a learned critic Q , a replay buffer $\mathcal{D}$, and a reference velocity field v_{ref} held fixed within each actor update. We first describe critic-guided velocity matching (Section IV-A), followed by the action-sensitive critic (Section IV-B) and the offline-to-online framework (Section IV-C).

A. Critic-Guided Velocity Matching

We instantiate the control objective with terminal score $r(x_1) = Q(s, x_1)$, holding the robot state s fixed throughout denoising. The actor-induced velocity correction relative to the reference is $\Delta v_\theta = v_\theta - v_{\text{ref}}$. Actor updates directly optimize the pretrained action expert v_θ . The terminal condition becomes

$$V(x_1, 1) = Q(s, x_1), \quad \nabla_x V(x_1, 1) = \nabla_A Q(s, x_1). \quad (4)$$

The optimal correction requires the value gradient at intermediate denoising states, whereas the critic is trained to evaluate clean action chunks. We connect these quantities through x_1^{ref} .

Estimating the value gradient with the critic. With $\dot{x}_u = v_{\text{ref}}(x_u, u)$, substituting (3) into the HJB equation and applying the chain rule gives

$$\begin{aligned} \frac{d}{du} V(x_u, u) &= \partial_u V + \nabla_x V^\top v_{\text{ref}} \\ &= -\frac{1}{2\rho} \|\nabla_x V(x_u, u)\|_2^2. \end{aligned} \quad (5)$$

Integrating (5) from τ to 1 and applying the terminal condition (4) yields

$$\begin{aligned} V(x_\tau, \tau) &= Q(s, x_1^{\text{ref}}) \\ &\quad + \frac{1}{2\rho} \int_\tau^1 \|\nabla_x V(x_u, u)\|_2^2 du. \end{aligned} \quad (6)$$

Thus, $Q(s, x_1^{\text{ref}})$ differs from $V(x_\tau, \tau)$ by a remaining-horizon correction. For fixed ρ and a locally bounded value gradient, this correction is $O(1 - \tau)$.

For locally smooth v_{ref} , x_1^{ref} admits the short-horizon expansion

$$\begin{aligned} x_1^{\text{ref}} &= x_\tau + \int_\tau^1 v_{\text{ref}}(x_u, u) du \\ &= \underbrace{x_\tau + (1 - \tau)v_{\text{ref}}(x_\tau, \tau)}_{\hat{x}_1^{\text{ref}}} + O((1 - \tau)^2). \end{aligned} \quad (7)$$

The leading-order term defines the one-step Euler look-forward estimate $\hat{x}_1^{\text{ref}}$.

Under local smoothness with bounded derivatives near $\tau = 1$, differentiating (6) and using the short-horizon expansion in (7) gives

$$\begin{aligned} \Delta v^*(x_\tau, \tau) &= \frac{1}{\rho} \nabla_x V(x_\tau, \tau) \\ &= \frac{1}{\rho} \nabla_A Q(s, \hat{x}_1^{\text{ref}}) + O(1 - \tau). \end{aligned} \quad (8)$$

The $O(1 - \tau)$ approximation error vanishes as $\tau \rightarrow 1$. We therefore use clean-action Q -gradients to construct critic-guided velocity corrections only at the last M denoising steps, without differentiating through v_{ref} .

Refining the Q-gradient correction. Let $\Delta_k = 1 - \tau_k > 0$ denote the remaining denoising time. Under the local Euler

Algorithm 1 Q-VGM: offline (top) and offline-to-online (bottom). The critic and buffer persist across the transition; only the backup target switches from (12) to (13). Q denotes the mean of current critic heads, and $\bar{Q}$ the minimum of target heads.

Offline Q-VGM

```

1:  $\mathcal{D} \leftarrow$  rollouts of  $\pi_{\theta_0}$  using (11)
2:  $\{Q_{\phi_i}\} \leftarrow$  critic trained on  $\mathcal{D}$  with the IQL backup (12);  $\theta_{\text{ref}} \leftarrow \theta_0$ 
3: for each gradient step do
4:   denoise with  $\theta$  (no grad):  $s \sim \mathcal{D}$ ;  $x_0 \sim \mathcal{N}(0, I)$ ;  $x_{\tau_{k+1}} \leftarrow x_{\tau_k} + (\tau_{k+1} - \tau_k) v_{\theta}(x_{\tau_k}, \tau_k, c)$ 
5:   for each late denoising step  $k = K - M, \dots, K - 1$  do
6:      $\hat{x}_1^{\text{ref}} \leftarrow x_{\tau_k} + \Delta_k v_{\text{ref}}(x_{\tau_k}, \tau_k, c)$ 
7:      $\hat{x}_1^Q \leftarrow$  improve  $\hat{x}_1^{\text{ref}}$  by normalized  $Q$ -gradient ascent
8:      $\ell_k \leftarrow \|\Delta v_{\theta}(x_{\tau_k}, \tau_k, c) - \text{sg}[\frac{\hat{x}_1^Q - \hat{x}_1^{\text{ref}}}{\Delta_k}]\|_2^2$ 
9:   end for
10:  update  $\theta$  once to minimize  $\mathcal{L}_{\text{align}} = \sum_{k=K-M}^{K-1} \ell_k$ 
11: end for

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$\triangleright$ exploration: latent temperature T , flow noise scale σ
 $\triangleright v_{\text{ref}} = v_{\theta_{\text{ref}}}$
 $\triangleright \Delta_k = 1 - \tau_k$
 $\triangleright$ one-step look-forward with the reference policy
 $\triangleright$ keep-best gate; freeze at first non-improvement
 $\triangleright$ gradients only through local v_{θ}
 $\triangleright$ critic discarded at inference

Offline-to-Online Q-VGM

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1:  $\theta, \{Q_{\phi_i}\}, \mathcal{D}$  from the offline phase;  $\theta_{\text{ref}} \leftarrow \theta$ 
2: for each cycle do
3:   (i) Rollout: collect  $B$  episodes with exploration noise, push to  $\mathcal{D}$ :
4:      $A \leftarrow x_1$  from the noisy flow rollout in (11)
5:   (ii) Critic:  $E$  TD epochs on minibatches  $(s, A, r, s', d) \sim \mathcal{D}$ :
6:      $A' \leftarrow \text{ODE}_{\theta}(s')$ 
7:      $y \leftarrow r + \gamma^H(1 - d)\bar{Q}(s', A')$ 
8:     update  $\phi$  to minimize  $\sum_i (Q_{\phi_i}(s, A) - y)^2$ 
9:   (iii) Actor (BPTT-free).  $\bar{Q} := \text{mean}_i Q_{\phi_i}$ 
10:    denoise with  $\theta$  (no grad):  $s \sim \mathcal{D}$ ;  $x_0 \sim \mathcal{N}(0, I)$ ;  $x_{\tau_{k+1}} \leftarrow x_{\tau_k} + (\tau_{k+1} - \tau_k) v_{\theta}(x_{\tau_k}, \tau_k, c)$ 
11:    for each late denoising step  $k = K - M, \dots, K - 1$  do
12:       $\hat{x}_1^{\text{ref}} \leftarrow x_{\tau_k} + \Delta_k v_{\text{ref}}(x_{\tau_k}, \tau_k, c)$ 
13:       $\hat{x}_1^Q \leftarrow$  improve  $\hat{x}_1^{\text{ref}}$  by normalized  $Q$ -gradient ascent
14:       $\ell_k \leftarrow \|\Delta v_{\theta}(x_{\tau_k}, \tau_k, c) - \text{sg}[\frac{\hat{x}_1^Q - \hat{x}_1^{\text{ref}}}{\Delta_k}]\|_2^2$ 
15:    end for
16:    update  $\theta$  once to minimize  $\mathcal{L}_{\text{align}} = \sum_{k=K-M}^{K-1} \ell_k$ 
17:   (iv) Reference update:  $\theta_{\text{ref}} \leftarrow$  EMA of  $\theta$ 
18: end for

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$\triangleright$ backup switches to (13)
 $\triangleright$ latent temperature T and per-step flow noise
 $\triangleright$ re-sampled from the current policy (no grad)
 $\triangleright$ targets $\bar{\phi}$ follow ϕ by EMA
 $\triangleright \Delta_k = 1 - \tau_k$
 $\triangleright$ one-step look-forward with the reference policy
 $\triangleright$ keep-best gate; freeze at first non-improvement
 $\triangleright$ gradients only through local v_{θ}
 $\triangleright$ slowly tracks the current policy

model in (7), the leading correction in (8) corresponds to a single endpoint update,

$$\hat{x}_1^{\text{direct}} = \hat{x}_1^{\text{ref}} + \frac{\Delta_k}{\rho} \nabla_A Q(s, \hat{x}_1^{\text{ref}}),$$

whose displacement divided by Δ_k recovers the direct velocity correction.

For a critic learned from limited robot experience, however, the Q -gradient norm need not indicate how far its local guidance can be trusted. A fixed gradient coefficient can produce excessive endpoint displacements into action regions poorly covered by the replay buffer, making the update sensitive to gradient scale. We therefore refine the endpoint with small normalized steps, decoupling the update length from the raw gradient magnitude.

Specifically, we sample $s \sim \mathcal{D}$ and $x_0 \sim \mathcal{N}(0, I)$, and denoise with the current actor. At each selected late step, we initialize $\hat{x}_1^{(0)} = \hat{x}_1^{\text{ref}}$ using (7) and propose up to J normalized Q -gradient steps:

$$\hat{x}_1^{(i+1)} = \hat{x}_1^{(i)} + \alpha \frac{\nabla_A Q(s, \hat{x}_1^{(i)})}{\|\nabla_A Q(s, \hat{x}_1^{(i)})\|_2},$$

where $\alpha > 0$ specifies the action-space step length. A keep-best gate accepts a proposal only if it strictly increases the estimated Q -value. Refinement stops at the first non-improving proposal or when the gradient vanishes. We

denote the last accepted endpoint by $\hat{x}_1^Q$, retaining $\hat{x}_1^{\text{ref}}$ if no proposal is accepted. The finite step budget bounds the total endpoint displacement by $J\alpha$.

Under the same Euler approximation, a local velocity correction shifts the predicted endpoint by $\Delta_k \widehat{\Delta v}_Q$. Equating this shift to the accepted endpoint displacement gives

$$\widehat{\Delta v}_Q(x_{\tau_k}, \tau_k) = \frac{\hat{x}_1^Q - \hat{x}_1^{\text{ref}}}{\Delta_k}. \quad (9)$$

We train the action expert to match these corrections:

$$\mathcal{L}_{\text{align}} = \sum_{k=K-M}^{K-1} \left\| \Delta v_{\theta}(x_{\tau_k}, \tau_k) - \widehat{\Delta v}_Q(x_{\tau_k}, \tau_k) \right\|_2^2. \quad (10)$$

The denoising states and constructed targets are detached, so gradients flow only through the local actor prediction v_{θ} .

B. Action-Sensitive Chunk Critic

Critic-guided velocity matching requires reliable action-space gradients $\nabla_A Q(s, A)$, where $A = [a_0, \dots, a_{H-1}]$ is a continuous normalized clean-action chunk. Following Q -chunking [39], we use a chunk-level critic trained on chunk-aligned transitions (s, A, r, s', d) with the discounted in-chunk return $r = \sum_{i=0}^{H-1} \gamma^i r_{t+i}$. The phase-specific critic backups are described in Section IV-C.

State representation. Following the $\pi_{0.5}$ architecture, we call the token sequence that the frozen VLM backbone

produces from the visual observation, language instruction, and proprioceptive state the VLA *prefix*. Feeding all prefix tokens into the critic is computationally impractical, so we compress the frozen prefix into an RL token z_{rl} , adopting the autoencoder architecture of Xu *et al.* [22]: the autoencoder is pretrained by reconstructing the prefix and then frozen, and the critic consumes z_{rl} from the frozen encoder. Because z_{rl} is high-dimensional relative to the action chunk, we re-inject A at every hidden layer of the critic, keeping the Q -network’s action pathway active for reliable $\nabla_A Q$.

C. Offline-to-Online RL Framework

Training proceeds in offline and online stages using a replay buffer $\mathcal{D}$. Both stages use the actor objective in (10), with phase-specific critic backups and reference updates (Algorithm 1).

Exploratory data collection. To populate $\mathcal{D}$ with diverse rollouts, collection uses latent temperature $T > 1$ and Gaussian *flow noise* with scale σ :

$$\begin{aligned} x_0 &\sim \mathcal{N}(0, T^2 I), \\ x_{\tau_{k+1}} &= x_{\tau_k} + \delta_k v_\theta(x_{\tau_k}, \tau_k, c) + \sigma \sqrt{\delta_k} \varepsilon_k, \end{aligned} \quad (11)$$

where $\delta_k = \tau_{k+1} - \tau_k$ and $\varepsilon_k \sim \mathcal{N}(0, I)$ independently. These exploration settings apply only to data collection. During training, actor-target construction and TD-target sampling use $T = 1$ and $\sigma = 0$; the same settings apply at evaluation.

Offline training. The offline stage uses a fixed buffer containing only exploratory rollouts of the pretrained policy. We use the fixed pretrained policy as the reference. Bootstrapping from actions outside the buffer’s support invites value over-estimation. We therefore use the in-support backup of implicit Q-learning (IQL) [37]: an action-free value head $V_{IQL}(s)$, fit by expectile regression toward the detached Q -estimate, provides the target

$$y = r + \gamma^H (1 - d) V_{IQL}(s'). \quad (12)$$

Online training. Online training resumes from the offline actor, critic, and replay buffer, adding new rollouts to $\mathcal{D}$ and updating the critic followed by the actor. We switch to a policy-sampled TD backup to evaluate actions from the evolving actor. The next action A' is re-sampled from the current policy by a clean denoising rollout (no gradient), and

$$y = r + \gamma^H (1 - d) \bar{Q}(s', A'), \quad (13)$$

where $\bar{Q}$ is the clipped (min) estimate of the target Q -heads [14].

During online training, we initialize the reference policy from the offline-trained actor and update its parameters through an exponential moving average (EMA). This allows the reference to adapt to the evolving actor rather than remain fixed at the pretrained checkpoint, while smoothing parameter changes across successive actor updates. The resulting reference velocity is used for look-forward estimation and critic-guided velocity matching. The reference parameters remain fixed within each actor update.

V. EXPERIMENTS

In this section, we evaluate Q-VGM by asking the following four research questions:

RQ1: How much can offline Q-VGM improve a few-shot SFT flow-matching VLA policy using only self-generated rollouts?

RQ2: Does offline Q-VGM outperform filtered behavior supervision, test-time selection, and test-time guidance under the same rollout data and critic?

RQ3: Can Q-VGM extend from offline to online training, and how does it compare with online RL fine-tuning in final success rate and sample efficiency?

RQ4: Does Q-VGM work on real bimanual manipulation tasks?

We answer these questions through simulation benchmarks and real-robot deployment.

A. Experimental Setup

Across all settings, we initialize $\pi_{0.5}$ with few-shot SFT: on Spatial, Object and Goal we use the few-shot SFT checkpoint released with π_{RL} [9], and on Long we fine-tune $\pi_{0.5}$ from the base model ourselves for 400 steps on 50 demonstrations (5 per task) in fp32.¹ All RL methods are trained by us from this initialization under identical conditions. For the LIBERO comparison, we run all offline and online methods with three independent training seeds to assess robustness across training runs. We evaluate each policy without exploration noise using 50 distinct evaluation seeds per task, with one rollout per seed (500 episodes per suite). The learning curves in Figs. 2 and 3 instead report the rollout success rate with exploration noise.

Offline. The SFT policy collects 150 rollout episodes per suite with the exploration noise of Algorithm 1. These rollouts alone form the fixed buffer for critic training and policy improvement, with no further interaction. No demonstrations are added to the RL buffer.

Offline-to-online. Training resumes from the offline policy, critic, and buffer, and collection is switched on, following the cycle of Algorithm 1.

Baselines. We compare against two groups, all starting from the same SFT checkpoint. The *offline group* uses the same rollout buffer and, where a critic is needed, shares ours: *Filtered BC**, flow-matching imitation of the successful rollouts; *RECAP*, advantage-conditioned self-training [21]; *Best-of-N*, which samples $N=8$ action chunks at inference and executes the highest-valued one under the critic [24], [25]; and *test-time Q guidance (QFQL)* [28], which applies QFQL’s inference-time guidance rule to the frozen SFT policy using our shared offline IQL critic. The *online group* interacts with the environment: *Diffusion-QL*, which adds a Q -maximization term backpropagated through the denoising

¹The released checkpoint and training pipeline use bf16 master weights; on the long-horizon suite we found this insufficient for any method to make progress, so all Long experiments (SFT and every RL method) are run in fp32.

chain to the diffusion BC loss [15] (BC + BPTT); its *BPTT-only* variant, which drops the BC term and is thus the pure critic-gradient update of TD3/SAC applied through the sampler (gradients reach the action expert, matching the trainable scope of Q-VGM); *Filtered BC**, online self-imitation on successful rollouts; and *PPO (flow-SDE)*, on-policy RL with a stochastic-flow likelihood surrogate [9].

Implementation details. For online LIBERO training, we use sparse rewards and an EMA reference policy across Spatial, Object, Goal, and Long. Table I summarizes key settings, including offline IQL and autoencoder pretraining. EMA coefficients denote the weight assigned to the current parameters.

TABLE I
KEY HYPERPARAMETERS FOR Q-VGM IN SIMULATION AND ON REAL ROBOTS.

Setting	LIBERO	Real robot	
Chunk length H	5	10	
Action dimension	7	14	
Q-head count	10	10	
Q-head widths	[512, 512, 256]	[512, 512, 256]	
RGB inputs	2 views	3 views	
Camera views	Wrist, third view	Front, left/right wrist	
Control	Delta EEF	Relative joint pose	
Shared Q-VGM		Offline IQL	
Denoising steps K	10	Training steps	6,000
Guided late steps M	5	Batch (frozen enc.)	64
Q-ascent steps J	3	Expectile τ_{IQL}	0.8
Ascent step α	0.05	Q LR	1×10^{-4}
Actor grad. clip	3.5	Value LR	1×10^{-4}
Discount γ	0.99	Critic target EMA	0.005
Online LIBERO		RL-token autoencoder	
Actor LR	5×10^{-6}	Training steps	10,000
Critic LR	3×10^{-4}	Batch size	32
Global batch	512	Learning rate	1×10^{-4}
Actor micro-batch	8	Encoder layers	2
Critic updates/actor	25	Decoder layers	2
Action pert. std.	0.05	Token dimension	2048
Reference EMA	0.002	Attention heads	8
Online suite setting	Spatial/Object/Goal	Long	
Latent temperature T	2.0	1.5	
Flow noise scale σ	0.08	0.15	
Critic target EMA	0.005	0.02	

B. Simulation Evaluation

This section addresses RQ1–RQ3 on the LIBERO Spatial, Object, Goal and Long suites [40].

Offline results (RQ1, RQ2). Table II shows that offline Q-VGM raises the four-suite average from 84.6% to 90.7% using only 150 noisy rollout episodes per suite and no additional expert data, outperforming every offline baseline. Behavior supervision on the same rollouts (Filtered BC 85.1%, RECAP 86.1%) recovers little, as it is bounded by the behaviors the policy already produces, and Best-of- N (86.5%) shows that re-ranking policy samples is similarly limited. Test-time Q guidance (QFQL) achieves 87.5% by querying the critic at intermediate noisy states during de-

TABLE II
LIBERO SUCCESS RATE (%) WITHOUT EXPLORATION NOISE (50 EPS/TASK, 500 EPS/SUITE). OFFLINE AND ONLINE METHODS: MEAN $\pm$ STD OVER THREE TRAINING SEEDS.

Method	Spatial	Object	Goal	Long	Avg
<i>Full-dataset SFT [9]</i>					
Octo [2]	78.9	85.7	84.6	51.1	75.1
OpenVLA [3]	84.7	88.4	79.2	53.7	76.5
OpenVLA-OFT [41]	91.6	95.3	90.6	86.5	91.0
π_0 -FAST [42]	96.4	96.8	88.6	60.2	85.5
π_0 [4]	96.8	98.8	95.8	85.2	94.2
$\pi_{0.5}$ [5]	98.8	98.2	98.0	92.4	96.9
<i>Few-shot SFT (initialization)</i>					
$\pi_{0.5}$ few-shot SFT	77.6	97.0	86.2	77.6	84.6
<i>Few-shot SFT + offline RL (150 rollout episodes per suite)</i>					
Filtered BC*	78.3 $\pm$ 0.7	97.1 $\pm$ 0.9	86.5 $\pm$ 1.8	78.5 $\pm$ 1.1	85.1 $\pm$ 0.6
RECAP [21]	79.9 $\pm$ 2.1	97.5 $\pm$ 0.8	87.8 $\pm$ 0.9	79.1 $\pm$ 2.4	86.1 $\pm$ 0.7
Best-of- N ($N=8$)	80.1 $\pm$ 2.0	97.0 $\pm$ 0.9	87.5 $\pm$ 1.8	81.3 $\pm$ 1.3	86.5 $\pm$ 1.1
QFQL (test-time) [28]	84.5 $\pm$ 1.9	97.1 $\pm$ 0.3	88.2 $\pm$ 1.7	80.2 $\pm$ 2.3	87.5 $\pm$ 1.2
Q-VGM (offline)	88.9$\pm$1.4	98.1$\pm$0.7	92.2$\pm$1.2	83.6$\pm$1.5	90.7$\pm$0.5
<i>Few-shot SFT + online RL</i>					
Diffusion-QL [15]	71.3 $\pm$ 4.5	86.5 $\pm$ 3.4	82.7 $\pm$ 3.9	70.1 $\pm$ 5.4	77.7 $\pm$ 3.2
Diffusion-QL (BPTT only)	33.4 $\pm$ 8.3	41.1 $\pm$ 10.2	36.9 $\pm$ 9.3	32.8 $\pm$ 10.2	36.1 $\pm$ 5.6
Filtered BC*	84.7 $\pm$ 1.9	99.1 $\pm$ 0.6	92.4 $\pm$ 1.6	85.0 $\pm$ 2.2	90.3 $\pm$ 0.8
PPO (flow-SDE) [9]	98.9 $\pm$ 0.6	99.9 $\pm$ 0.1	97.7 $\pm$ 0.9	93.1 $\pm$ 0.8	97.4 $\pm$ 0.3
Q-VGM (online)	99.8$\pm$0.2	99.9$\pm$0.1	99.4$\pm$0.6	94.6$\pm$0.3	98.4$\pm$0.2

*Filtered BC imitates successful policy-generated trajectories.

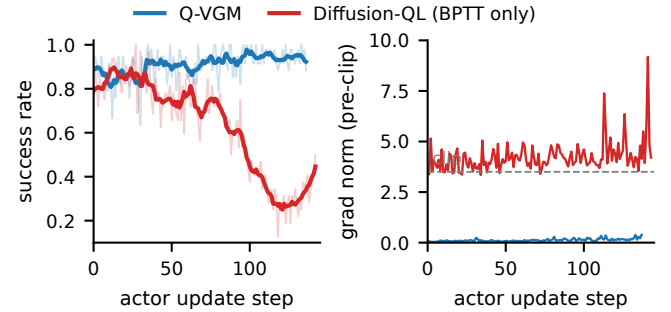


Fig. 2. Q-VGM vs. Diffusion-QL (BPTT only) on LIBERO-Long task 2: rollout success rate with exploration noise (left) and actor gradient norm before clipping (right).

noising and directly using the resulting action gradients to guide sampling.

Online results (RQ3). Across three training seeds, online Q-VGM achieves a four-suite average success rate of $98.4 \pm 0.2\%$. This exceeds PPO with flow-SDE (97.4%) and the $\pi_{0.5}$ policy fine-tuned on the full demonstration dataset (96.9%; Table II). Diffusion-QL with its BC term achieves 77.7%, below the SFT initialization; removing the BC term (BPTT only) further reduces success to 36.1%. In Fig. 2, the BPTT-only update collapses, with actor gradient norms an order of magnitude above Q-VGM’s.

Sample efficiency (RQ3). Table III reports episode budgets for 95% rollout success rate with exploration noise on four LIBERO task suites. PPO uses $4.43\text{--}6.14\times$ as many episodes; the arithmetic mean of the four ratios is $5.35\times$.

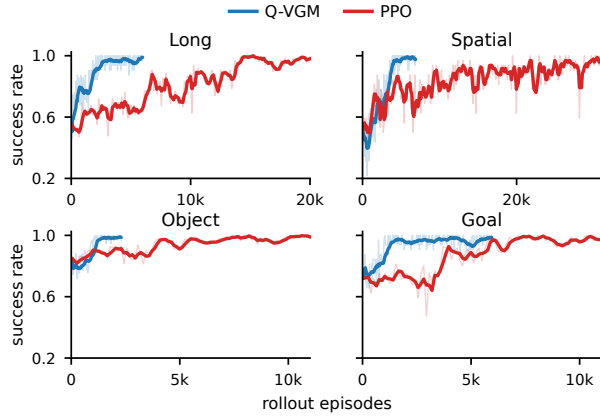


Fig. 3. Sample efficiency of Q-VGM and PPO on LIBERO. Curves show one training run per method using the same random seed value and report the rollout success rate with exploration noise.

TABLE III

EPISODE BUDGETS FOR 95% ROLLOUT SUCCESS RATE. BOTH METHODS REPORT MEAN EPISODE BUDGETS OVER THREE TRAINING SEEDS. Q-VGM INCLUDES THE 150 OFFLINE ROLLOUT EPISODES PER SUITE.

Suite	Q-VGM	PPO	PPO / Q-VGM
Spatial	3,968.7	21,269.3	5.36×
Object	1,152.7	7,072.0	6.14×
Goal	1,291.3	5,717.3	4.43×
Long	2,518.0	13,770.7	5.47×

C. Real-Robot Evaluation

Setup. This section addresses RQ4. We evaluate three bimanual manipulation tasks on a real robot (Fig. 4): Handover Mic, Pick Cup, and Lift Pot. The $\pi_{0.5}$ policy is initialized by few-shot SFT with 10 demonstrations per task; the SFT policy then collects 100 rollout episodes per task for the offline phase, and every method is evaluated over 20 trials per task on in-distribution initial configurations. The offline baselines follow the same protocol as in simulation.

TABLE IV

REAL-ROBOT SUCCESS RATES (SUCCESSES / 20 TRIALS) ON HANDOVER MIC, PICK CUP AND LIFT POT. ALL METHODS START FROM THE SAME FEW-SHOT SFT POLICY (10 DEMONSTRATIONS PER TASK) AND USE THE SAME 100 ROLLOUT EPISODES PER TASK.

Method	Mic	Cup	Pot
SFT	12/20	15/20	13/20
Filtered BC*	15/20	17/20	15/20
RECAP [21]	16/20	17/20	15/20
Best-of- N	15/20	16/20	18/20
Test-time Q guidance (QFQL) [28]	16/20	16/20	17/20
Q-VGM (offline)	19/20	20/20	20/20

*Filtered BC imitates successful policy-generated trajectories.

Results. Offline Q-VGM uses the IQL training settings in Table I and 500 actor updates. Table IV shows that offline Q-VGM improves success rates on all three tasks from 12/20, 15/20, and 13/20 to 19/20, 20/20, and 20/20, respectively, outperforming all offline baselines. These real-robot results, together with the sample-efficiency gains in simulation,



Fig. 4. Real-robot bimanual manipulation tasks.

suggest that Q-VGM’s off-policy learning is well suited to real-world VLA fine-tuning, where robot interactions are costly.

D. Ablation Studies

We ablate the offline critic objective on LIBERO-Spatial, holding the rollout buffer, RL-token state, and actor update fixed (Table V).

TABLE V

OFFLINE CRITIC-OBJECTIVE ABLATION ON LIBERO-SPATIAL.

Critic objective	Spatial SR (%)
IQL (ours) [37]	88.9
CQL [43]	87.8
SARSA [44]	87.0
Cal-QL [13]	84.5

Table VI reports online component ablations on LIBERO-Spatial. Matching at all denoising steps reduces success from 99.8% to 96.2%, and removing the keep-best gate reduces it to 95.0%. Using the current actor for target construction yields 82.0% and leads to highly unstable training, with large performance fluctuations.

TABLE VI

ONLINE Q-VGM COMPONENT ABLATIONS ON LIBERO-SPATIAL.

Variant	Spatial SR (%)
Full Q-VGM	99.8
Matching at all denoising steps	96.2
Without keep-best (fixed J steps)	95.0
Current actor for target construction	82.0

VI. CONCLUSION

We presented Q-VGM, a sample-efficient off-policy RL method that fine-tunes flow-matching VLA policies with a learned critic, requiring neither action likelihoods nor backpropagation through the denoising chain. Casting policy improvement as optimal control over the denoising dynamics, Q-VGM constructs critic-guided velocity corrections from look-forward actions to fine-tune the action expert, and trains a single critic across the offline and online phases with only the backup target switched. Offline Q-VGM improves a few-shot-SFT $\pi_{0.5}$ policy from 84.6% to 90.7% on LIBERO and from 66.7% to 98.3% on three real bimanual manipulation tasks, and offline-to-online training reaches 98.4%, surpassing PPO fine-tuning. To reach 95% rollout success across the four LIBERO suites, PPO requires 5.3× as many episodes on average as Q-VGM.

Limitations and future work. Q-VGM relies on the critic’s action-space gradient, which is most trustworthy near actions supported by the buffer; keep-best selection falls back to the base action when ascent does not improve the value, but a stronger safeguard would internalize a trust region into the sampling dynamics [36]. Scaling the critic to longer horizons and more diverse environments also remains challenging [45]; combining world models with value estimation, so that a learned dynamics model shortens the effective TD horizon while the value function keeps supplying gradient signals, is a promising direction.

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