

ManiCM: Real-time 3D Diffusion Policy via Consistency Model for Robotic Manipulation

Guanxing Lu¹, Zifeng Gao^{1*}, Tianxing Chen², Wenxun Dai¹, Ziwei Wang³, Wenbo Ding¹, Yansong Tang^{1†}

¹Tsinghua Shenzhen International Graduate School, Tsinghua University

² Shanghai AI Laboratory, ³ Nanyang Technological University

{lgx23@mails., tang.yansong@sz.}tsinghua.edu.cn

{konbi.gao, chentianxing2002, wxdai2001}@gmail.com, ziwei.wang@ntu.edu.sg

<https://ManiCM-fast.github.io>

Abstract—Diffusion models have been verified to be effective in generating complex distributions from natural images to motion trajectories. Recent diffusion-based methods show impressive performance in 3D robotic manipulation tasks, whereas they suffer from severe runtime inefficiency due to multiple denoising steps, especially with high-dimensional observations. To this end, we propose a real-time robotic manipulation model named ManiCM that imposes the consistency constraint on the diffusion process, so that the model can generate robot actions in only one-step inference. Specifically, we formulate a consistent diffusion process in the robot action space conditioned on the point cloud input, where the original action is required to be directly denoised from any point along the ODE trajectory. To model this process, we design a consistency distillation technique to predict the action sample directly instead of predicting the noise within the vision community for fast convergence in the low-dimensional action manifold. We evaluate ManiCM on 31 robotic manipulation tasks from Adroit and Metaworld, and the results demonstrate that our approach accelerates the state-of-the-art method by 10 times in the average inference speed while maintaining competitive average success rate.

I. INTRODUCTION

Designing robots for diverse manipulation tasks has been highly desired in the robotic community for a long time. In this pursuit, previous arts have made great progress in exploring different architectures, e.g., perceptive models like convolutional networks [1], [2], transformers [3], [4], and generative models like diffusion models [5], [6], [7]. Among these choices, diffusion-based policies receive increasing attention for their capacity to model diverse high-dimensional robotic trajectories, where robot observation is provided as the condition for generation. For instance, diffusion models have been extensively utilized across various domains as high-level procedure planners [8], [9], [10], [11], [12], low-level motion policies [13], [14], [5], [15], [16], [17], teacher models [18], [19], and data synthesis engines [20], [21], [22], demonstrating impressive performance in diverse robotic tasks.

However, diffusion-based fashions inevitably suffer from severe runtime inefficiency by requiring considerable sampling steps for high-quality action synthesis during inference, even with some sampling acceleration [24]. As shown in Figure 1, the diffusion policy (DP [5]) requires ~ 162 ms per step to generate a high-quality action. Moreover, the 3D diffusion

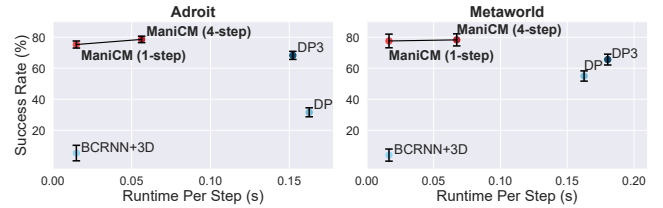


Fig. 1: Trade-off Between Efficiency and Effectiveness. We present ManiCM, a real-time 3D diffusion policy by imposing the consistency constraint on the diffusion process. BCRNN+3D [23] is a state-of-the-art perceptive model-based behavior cloning agent augmented with 3D point cloud input. DP [5] and DP3 [6] are the state-of-the-art diffusion-based manipulation agents. ManiCM achieves a decision-making runtime of 17ms, which is $10\times$ faster than previous mainstream methods.

policy (DP3 [6]) only achieves a decision latency of ~ 178 ms when dealing with the high-dimensional 3D point cloud input, which blocks the applications of real-time closed-loop control. To address this issue, recent efforts have been proposed to speed up the inference phase of diffusion models by hierarchical sampling [25], [15], [16]. Nevertheless, it is hard to determine the hierarchy across task domains that exhibit different challenging levels, which limits the practicality of the existing works to 3D robotic manipulation.

Recently, the concept of consistency models [26], [27] has been introduced in image generation, which synthesizes high-fidelity images with a minimal number of steps. In this paper, we propose a ManiCM method that leverages the concept of consistency models for real-time robotic manipulation. Different from existing methods that focus on designing hierarchical planning for specific domains, we design a generalizable consistency distillation technique to generate robot actions in only one-step inference. More specifically, we first formulate a diffusion process to denoise robot action conditioned on the point cloud, and then ensure the consistency property that the original action can be directly denoised from any point along the ODE trajectory. Then, we utilize the consistency distillation technique to predict the action sample directly, based on the observation that predicting the denoised action converges faster than predicting the noise in the vision community. We evaluate ManiCM on a diverse set of robotic manipulation tasks from

Adroit and Metaworld, and the results illustrate that our approach achieves an average inference speed acceleration of $10\times$ compared to the state-of-the-art method, while still maintaining competitive average success rates (Figure 1). We introduce consistency distillation into the robotic manipulation area and accelerate high-quality 3D manipulation action generation to a real-time level. Our contributions can be concluded as follows: itemindent = 0pt, leftmargin=0.5cm

- We propose a real-time 3D diffusion policy to learn robot action conditioned on the point cloud, so that the original action can be directly denoised from any point along the ODE trajectory.
- We design a manipulation consistency distillation technique to predict the action sample directly instead of predicting the noise for fast convergence to the action manifold.
- Extensive experiments on 31 robotic manipulation tasks from Adroit and Metaworld demonstrate that our approach accelerates the state-of-the-art method by a large margin in average inference speed while maintaining competitive average success rates.

II. RELATED WORK

A. Diffusion Models for 3D Robotic Manipulation

The exploration of the most effective architecture for end-to-end robotic manipulation has been a long-standing process. The trended architectures include convolution networks [1], [2], transformers [3], [4], and diffusion models [8], [9], [10], [11], [12], [13], [14], [5], [20], [21], [22], [6], [16], [17]. Among these, diffusion models first emerged as a transformative approach in image generation [28], [24], leveraging the iterative refinement of Gaussian noise into data samples. Recently, they have been introduced to the field of embodied AI, and have made significant progress in applications that demand nuanced decision-making and adaptive control. Specifically, [5], [8], [9] first demonstrated the potential of the diffusion model in low-dimensional control tasks. Furthermore, the diffusion model classes [6], [29], [16], [17] are extended to more complex 3D robotic manipulation tasks, and also achieve superior performance to other traditional architectures. However, applying diffusion models to 3D robotic manipulation faces the issue of insufficient decision-making frequency. 3D tasks involve complex spatial representations, which pose significant challenges for real-time robotic operation and control. Denoising processes are effective at generating high-fidelity outputs, but their iterative nature can be computationally expensive, creating a conflict between thorough exploration of the solution space and the need for fast decision-making in dynamic robotic tasks. To solve this issue, recent methods present to skip inference steps by hierarchical sampling [25], [15], [16], while it is hard to determine the hierarchy across different domains. In this paper, we harness the power of the consistency model [26] to improve the efficiency of diffusion models in 3D decision-making, utilizing point clouds as effective 3D representations.

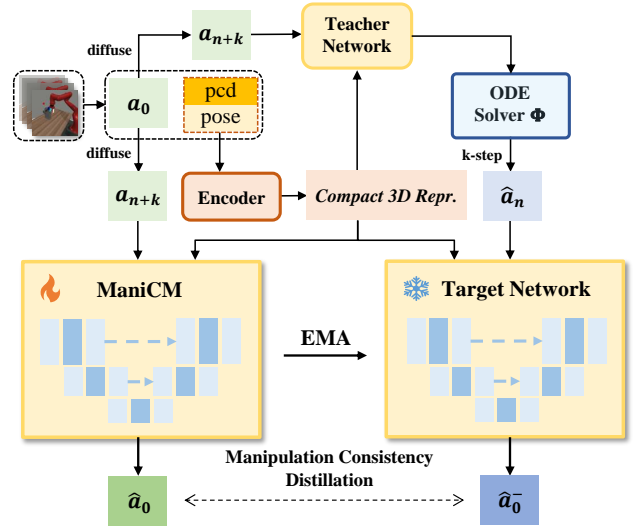


Fig. 2: **Overall Pipeline.** Given a raw action sequence a_0 , we first perform a forward diffusion to introduce noise over $n + k$ steps. The resulting noisy sequence a_{n+k} is then fed into both the online network and the teacher network to predict the clean action sequence. The target network uses the teacher network's k -step estimation results to predict the action sequence. To enforce self-consistency, a loss function is applied to ensure that the outputs of the online network and the target network are consistent.

B. Consistency Models

To accelerate the sampling speed of the current diffusion models (DMs) [30], [28], [31], [32], the concept of consistency models (CMs) [26] was first introduced in the image generation domain. The core idea behind the consistency models is to enforce the model to learn to map any point at any time to the origin of the probability flow ODE (PF-ODE) trajectory, *i.e.*, the clean image. The consistency model facilitates efficient image generation, allowing trade-offs between extremely few inference steps and the generation quality. Recently, latent consistency models (LCMs) [27], [33] successfully distilled from the Stable Diffusion [32], achieving significant acceleration in the speed of text-conditioned image generation. Based on LCMs, [34], [35] introduce diverse conditional controls to manipulate the text-to-image latent consistency models. Moreover, the consistent model has been introduced in various research domains such as video [36], [37], 3D human motion [38], and audio [39], unlocking new capabilities for various real-time applications. While initial success has been achieved in incorporating relatively simple embodied tasks with the consistency model, as explored in [40], [41], [42], its application to complex robotic manipulation tasks with high-dimensional 3D visual conditions still remains largely unexplored. To fill this research gap, we propose ManiCM to achieve real-time 3D diffusion policy generation for the first time.

III. APPROACH

In this section, we first present the problem formulation and the preliminaries on consistency models (Section III-A). Then, we present an overview of our pipeline, and

detail the design of each component in the manipulation consistency model (Section III-B). To enable our model to learn consistent generation from the teacher network, we propose the manipulation consistency distillation (Section III-C).

A. Problem Formulation

The demand for robotic manipulation is of great significance in the pursuit of the general embodied agent. To train a manipulation agent, we focus on imitation learning that learns a policy from a limited set of expert demonstrations. The policy $\pi : \mathcal{O} \mapsto \mathcal{A}$ maps the observation $o \in \mathcal{O}$ to the robot action $\mathbf{a} \in \mathcal{A}$. The observation contains the point cloud received from an eye-to-hand RGB-D camera and the robot proprioception data. ManiCM uses sparse point clouds as the 3D representation. Based on the 3D visual input $o^{(t)}$ and the robot poses, the agent is required to generate the optimal action for the robot arm and grippers $\mathbf{a}^{(t)}$, which respectively demonstrates the change in 3D space of the end-effector followed by a normalized torque that the gripper fingers should apply. While existing diffusion models produce high-quality robot actions, their iterative inference limits real-time 3D manipulation. Therefore, we propose a framework based on the consistency model to enhance decision efficiency.

The Consistency Model (CM) [26] introduces an efficient generative model designed for effective single-step or few-step inference generation while maintaining a comparable performance. Given a PF-ODE that can transfer data into noise, the objective of CM is to learn the solution function $\mathbf{f}(\cdot, \cdot)$ of this PF-ODE, such that any point on the ODE trajectory, can be mapped back to the original distribution through $\mathbf{f}(\cdot, \cdot)$. Given a solution trajectory $\{\mathbf{x}_t\}_{t \in [\epsilon, T]}$ of the PF-ODE, the consistency function \mathbf{f} is defined as $\mathbf{f} : (\mathbf{x}_t, t) \mapsto \mathbf{x}_\epsilon$, where $t \in [0, T]$, $T > 0$ is a fixed constant. To avoid potential numerical instability at zero, ϵ is a very small fixed positive number instead of zero, and \mathbf{x}_ϵ can be regarded as an approximation of the data distribution ($\hat{\mathbf{x}}_\epsilon \sim p_{\text{data}}(\mathbf{x})$). According to [26], the consistency function should satisfy the self-consistency property defined as:

$$\mathbf{f}(\mathbf{x}_t, t) = \mathbf{f}(\mathbf{x}_{t'}, t'), \forall t, t' \in [\epsilon, T]. \quad (1)$$

As shown in Equation (1), the implication of the self-consistency property is that for any input pairs (\mathbf{x}_t, t) on the same PF-ODE trajectory, their outputs $\mathbf{f}(\mathbf{x}_t, t)$ remain consistent. All consistency models have to meet the boundary condition $\mathbf{f}(\mathbf{x}_\epsilon, \epsilon) = \mathbf{x}_\epsilon$, as it plays an important role in the success of consistency model training, according to [26]. To impose the self-consistency property on deep neural networks, we implement function $\mathbf{f}(\cdot, \cdot)$ as:

$$\mathbf{f}_\theta(\mathbf{x}, t) = c_{\text{skip}}(t)\mathbf{x} + c_{\text{out}}(t)\mathbf{F}_\theta(\mathbf{x}, t), \quad (2)$$

where $c_{\text{skip}}(t)$ and $c_{\text{out}}(t)$ are differentiable functions with $c_{\text{skip}}(\epsilon) = 1$ and $c_{\text{out}}(\epsilon) = 0$, and $\mathbf{F}_\theta(\cdot, \cdot)$ is a parametrized deep neural networks to learn the self-consistency. *Consistency Distillation* is a method for training CM by distilling knowledge from pre-trained diffusion models (*i.e.*, the ‘teacher

network’). The consistency loss is defined as:

$$\mathcal{L}(\theta, \theta^-; \Phi) = \mathbb{E} [d(\mathbf{f}_\theta(\mathbf{x}_{t_{n+1}}, t_{n+1}), \mathbf{f}_{\theta^-}(\hat{\mathbf{x}}_{t_n}^\Phi, t_n))], \quad (3)$$

where $d(\cdot, \cdot)$ is a metric function chosen for measuring the distance between two samples. $\mathbf{f}_\theta(\cdot, \cdot)$ and $\mathbf{f}_{\theta^-}(\cdot, \cdot)$ are referred to as ‘online network’ and ‘target network’ according to [26]. When the optimization of the online network converges, the target network will eventually match the online network since θ^- is a running average of θ .

B. ManiCM: Manipulation Consistency Model

3D Conditional Generation. To incorporate the rich spatial information embedded in the 3D point cloud, we propose to inject the point cloud representation into the diffusion policy as conditions. Specifically, given the depth image received from a single-view RGB-D camera, we first obtain the point cloud by the extrinsic and intrinsic of the camera. We down-sample the point cloud via farthest point sampling, in order to focus on the interest region like the robot arm and targets. Then, the sparse point cloud is encoded by a carefully designed MLP point cloud encoder, resulting in a compact 3D representation. Subsequently, we condition the original diffusion model with the compact 3D representation, which can be expressed as:

$$\mathbf{a}^{t-1} = \alpha_t (\mathbf{a}^t - \gamma_t \epsilon_\theta (\mathbf{a}^t, t, p, q)) + \sigma_t \mathcal{N}(0, \mathbf{I}), t > 0, \quad (4)$$

where ϵ_θ is the predicted noise. p and q denote point cloud conditions and robot poses, respectively.

Manipulation Self-Consistency Function. However, the iterative procedure in Equation (4) raises a non-negligible computational burden, especially with high-dimensional point cloud conditions. To this end, we propose to constrain the original action to be recovered from any point along the trajectory, so that the model can generate action in only one step in the test phase:

$$\mathbf{a}^0 = c_{\text{skip}}(t)\mathbf{a}^t + c_{\text{out}}(t)\mathbf{F}_\theta(\mathbf{a}^t, t, p, q), t \geq 0, \quad (5)$$

where \mathbf{F}_θ is a manipulation consistency function that contains the accumulated ϵ_θ in Equation (4) along the trajectory. In practice, $c_{\text{skip}}(t) = \sigma_d^2 / (\beta^2 t^2 + \sigma_d^2)$, $c_{\text{out}}(t) = \beta t / \sqrt{(\beta^2 t^2 + \sigma_d^2)}$, where β denotes a timestep scaling value while σ_d is a balance value. The $\mathbf{F}_\theta(\cdot, \cdot)$ can be parametrized to predict the action sample or the noise epsilon. In mainstream diffusion generation works for image generation, the default prediction type is noise rather than sample. We speculate that while directly predicting samples may intuitively yield higher-quality generated outputs [43], predicting the distribution of images is much more challenging for denoising models in high-dimensional image space. However, the dimensionality of the robot action is quite small (approximately 28) in manipulation tasks. In this scenario, directly learning the distribution of the samples is relatively easy and brings low variance and fast convergence, echoing [6]. More importantly, the large prediction variance caused by predicting noise will be amplified in consistency models. Specifically, the consistency property encourages the $\mathbf{f}_\theta(\mathbf{a}_n, t_n)$ to match $\hat{\mathbf{a}}_0 = \mathbf{f}_\theta(\mathbf{a}_0, t_0)$, while the original diffusion model only

TABLE I: **Comparisons on Runtime.** We evaluate 100 episodes on 31 challenging tasks from Adroit and Metaworld across 3 random seeds and report the time consumption per step (s) with standard deviation. The second results are underlined and the best results are bold. “*” denotes the reproduced version. The performance of our ManiCM in one-step inference surpasses all state-of-the-art models, providing ample evidence for the effectiveness of consistency distillation.

Method	NFE	Adroit (3)	Metaworld Easy (18)	Metaworld Medium (3)	Metaworld Hard (3)	Metaworld Very Hard (4)	Average
DP	10	-	-	-	-	-	162.6±1.2
Image-based ManiCM (1-step)	1	14.9	16.2	16.1	15.5	16.3	16.0±0.1
Voxel-based DP	10	183.6	205.3	192.2	198.8	211.5	202.1±1.1
Voxel-based ManiCM (1-step)	1	18.1	20.0	20.6	20.5	20.8	20.0±0.2
BC-GMM+3D	1	14.7	15.9	16.1	15.8	16.9	15.9±0.7
BC-RNN+3D	1	14.9	16.8	16.2	16.4	16.4	16.6±0.5
DP3	10	159.6	177.4	186.1	183.2	181.8	177.6±1.4
Simple DP3	10	95.5	123.5	119.2	124.6	124.7	120.6±0.9
DP3 (4-step)	4	52.6	66.5	76.3	58.6	62.1	64.9±0.9
Simple DP3 (4-step)	4	27.3	34.4	33.6	35.6	34.2	33.6±0.5
ManiCM (1-step)	1	16.9	17.6	17.2	17.0	16.5	17.3±0.1
ManiCM (4-step)	4	56.3	66.8	68.2	67.9	69.4	66.2±0.3

TABLE II: **Comparisons on Success Rate.** We evaluate 100 episodes on 31 challenging tasks from Adroit and Metaworld across 3 random seeds and report the success rates (%) with standard deviation. The second results are underlined and the best results are bold. “*” denotes the reproduced version. The performance of our ManiCM in one-step inference surpasses all state-of-the-art models, providing ample evidence for the effectiveness of consistency distillation.

Method	NFE	Adroit (3)	Metaworld Easy (18)	Metaworld Medium (3)	Metaworld Hard (3)	Metaworld Very Hard (4)	Average
DP	10	31.6	77.1	18.0	3.0	22.5	52.8±3.6
Image-based ManiCM (1-step)	1	32.2	77.5	18.9	4.3	21.5	53.1±3.9
Voxel-based DP	10	35.7	80.2	24.5	12.4	30.8	57.5±3.1
Voxel-based ManiCM (1-step)	10	36.4	80.5	24.9	11.5	31.5	57.8±3.8
BC-GMM+3D	1	3.8	4.7	3.8	3.4	3.4	4.2±0.4
BC-RNN+3D	1	4.1	4.5	3.8	3.2	3.0	4.0±0.5
DP3	10	76.1	91.7	46.3	44.8	62.3	77.5±3.8
Simple DP3	10	73.0	90.4	47.3	45.6	56.5	75.8±3.3
DP3 (4-step)	4	75.3	86.1	39	44.0	61.3	72.4±2.6
Simple DP3 (4-step)	4	73.0	84.3	37.3	43.3	62.0	70.9±3.3
ManiCM (1-step)	1	74.9	92.9	47.7	44.2	65.7	78.5±4.2
ManiCM (4-step)	4	78.2	93.0	48.0	46.7	64.5	79.0±3.9

requires $\hat{\mathbf{a}}_n$ to be close to $\hat{\mathbf{a}}_{n-1}$. Thus, the variance is propagated along the ODE trajectory in consistency modeling, which ultimately blocks the convergence of prediction noise in manipulation tasks (Figure 3). Therefore, we parameterize the manipulation self-consistency function $\mathbf{F}_\theta(\cdot, \cdot)$ to predict the action sample rather than noise.

C. Manipulation Consistency Distillation

To train ManiCM, we adopt the method of consistency distillation, as depicted in Figure 2. Here \mathbf{a}_0 represents the sequence of robotic arm actions, which comprises multiple actions, with the dimensionality determined by the specific task. pcd denotes the point cloud obtained from images while $pose$ signifies the current pose of the robotic arm from the offline dataset. These inputs are processed through an encoder to obtain compact representations, which are then used as conditional inputs for the teacher network, online network, and target network. Given a ground-truth expert action \mathbf{a}_0 , we first obtain the noisy action \mathbf{a}_{n+k} by conducting a forward diffusion operation with $n+k$ steps to add noise to \mathbf{a}_0 , where k is the skipping interval mentioned in Section III-A. Subsequently, the noisy action \mathbf{a}_{n+k} is feed-forwarded to a frozen teacher network and the online network to decode the clean $\hat{\mathbf{a}}_0^*$ and $\hat{\mathbf{a}}_0$, respectively. In order to make sure the

self-consistency property Equation (1), we design a target network cloned from the online network, and we expect the denoised outputs of the online network and the target network to be aligned. Specifically, the target network generates $\hat{\mathbf{a}}_0^-$ utilizing \mathbf{a}_n obtained from processing $\hat{\mathbf{a}}_0^*$ with a k -step ODE solver Φ (e.g., DDIM [24]), such that $\hat{\mathbf{a}}_0$ and $\hat{\mathbf{a}}_0^-$ are obtained by the consistency function $\mathbf{f}(\cdot, \cdot)$ in Equation (2). Therefore, the consistency distillation loss is expressed as,

$$\mathcal{L}_{\text{MCD}}(\theta, \theta^-) = \mathbb{E} \left[\left\| \mathbf{f}_\theta(\mathbf{a}_{n+k}, t_{n+k}) - \mathbf{f}_{\theta^-}(\hat{\mathbf{a}}_n^\Phi, t_n) \right\|_2^2 \right], \quad (6)$$

where $\|\cdot\|_2$ is the ℓ_2 norm. Besides, θ^- is updated with the exponential moving average (EMA) of the parameter θ defined as $\theta^- \leftarrow \text{sg}(\mu\theta^- + (1-\mu)\theta)$, where $\text{sg}(\cdot)$ denotes the stopgrad operation and μ satisfies $0 \leq \mu < 1$. In Equation (6), $\hat{\mathbf{a}}_n^\Phi$ is the k -step estimation from \mathbf{a}_{n+k} . Therefore, the $\hat{\mathbf{a}}_n^\Phi$ can be formulated as,

$$\hat{\mathbf{a}}_n^\Phi \leftarrow \mathbf{a}_{n+k} + (t_n - t_{n+k})\Phi(\mathbf{a}_{n+k}, t_{n+k}), \quad (7)$$

where $\Phi(\cdot, \cdot)$ is the update function of a k -step ODE solver applied to PF-ODE. As outlined in Section III-A, we utilize EMA to update the parameters of the target network from the parameters of the online network. We refer to the pre-trained

manipulation 3D diffusion model, such as DP3 [6], as the "teacher network".

Compared to other manipulation diffusion models, our ManiCM model achieves the fastest runtime (**$\sim 16\text{ms}$ per action**) during the inference phase by sampling high-quality actions in just one step, which is illustrated in Table I.

IV. EXPERIMENTS

In this section, we first introduce the experiment setup including datasets, baseline methods, evaluation metrics and implementation details (Section IV-A). Then we compare our method with the state-of-the-art approaches to show the superiority in runtime efficiency and success rate on simulation environment (Section IV-B) and real-world environment (Section IV-C). Subsequently, we conduct an ablation study to explore different design choices in our ManiCM (Section IV-D). We also illustrate the visualization results to depict our intuition (Section IV-E). Further results can be found in the supplementary material.

A. Experimental Setup

Datasets. We conduct our single-task experiments in the well-recognized MetaWorld [44] and Adroit [45] benchmarks, resulting in a total of 31 tasks. These tasks range from simple pick-and-place tasks to more challenging scenarios such as dexterous manipulation, which ensure that the model is effective across various scenarios. Specifically, MetaWorld tasks are grouped into different difficulty levels from easy to very hard according to [46]. For offline training datasets, we obtain expert demonstrations through heuristic policies in MetaWorld, and acquire them utilizing the reinforcement learning method VRL3 [47] in Adroit. We obtain a limited number of 10 expert demonstrations for training in each benchmark, following [6] for fair comparisons. We also conduct multi-task experiments on eight high-quality tasks selected from RL Bench [48] benchmark. All models are trained with 20 demonstrations per task and use only the front camera view following [29].

Baselines. This work primarily emphasizes accelerating the inference speed of 3D modality in diffusion policy to achieve real-time robotic action generation. To this end, our main baseline is the state-of-the-art point cloud-based 3D diffusion policy (DP3 [6]). Additionally, we compare our method with 'Simple DP3', a variation of DP3 with a lightweight policy backbone. Our baselines also include the well-known diffusion policy (DP [5]) and 3D Diffuser Actor (3dda [29]) for more comprehensive performance comparisons. To ensure fairness, the resolution of all images and depth maps remains consistent across all experiments.

Evaluation Metrics. Following [6], we assess 20 episodes every 200 training epochs and then calculate the average of the highest 5 success rates, along with the average runtime per step. For each main experiment, we run 3 random seeds with seed numbers 0, 1, 2 to mitigate the performance fluctuation. We also report the Number of Function Evaluations (NFE) as an additional device-agnostic metric for inference speed.

For the success rate and runtime, the higher the better. For the NFE, the lower the better.

Implementation Details. For ManiCM, an AdamW [49] optimizer with a batch size of 128 and a learning rate of $5e-5$ is employed for 3K epochs training. We also adopt a cosine decay learning rate scheduler and 500 iterations of linear warm-up. The EMA rate is set to $\mu = 0.95$ by default and we use DDIM-Solver [24] with a skipping step of $k = 10$ as ODE Solvers. Unless otherwise specified, our experiments are conducted using 100 training time steps. The teacher model employed in our experiments uses DDIM with an inference step of 10. For the input, We utilize an observation steps value of 2, indicating that we use the point clouds from the two most recent time steps as conditions. Similarly, with a horizon of 4, we predict four consecutive actions during each iteration for long-horizon tasks, while only 2 actions are executed per prediction. To focus on the interest area, the image size is cropped to 84×84 pixels. The point cloud is downsampled to 512 points using the Farthest Point Sampling (FPS) algorithm, while the dimension of agent poses and actions are determined by the specific task. Both point clouds and agent poses are encoded using an MLP encoder into embeddings of length 64. For normalization, we limit the min and max of action and observation to $[-1, 1]$ independently since the prediction of DDIM would clip the prediction to $[-1, 1]$ to ensure training stability. We implement our model in PyTorch [50], and all compared models are trained and evaluated on one NVIDIA RTX 4090 GPU to benchmark the decision runtime.

B. Comparison with the State-of-the-Art Methods

In this section, we compare ManiCM with existing state-of-the-art methods on Adroit and Metaworld to demonstrate the effectiveness of our method.

Comparisons on Runtime. Table I illustrates the comparison of the runtime per step of each model. Our method achieves an impressive runtime around **16ms per step** on average, which is $\sim 10\times$ faster than the baseline method DP3. The acceleration comes from the manipulation consistency model, which can generate robot actions in only one-step inference. Besides, the 4-step inference version of ManiCM also improves the efficiency by $\sim 3\times$. Moreover, the proposed ManiCM also surpasses the lightweight version Simple DP3 significantly, which shows that the speedup from reducing the sampling speed is a more efficient way than shrinking the model itself. The results demonstrate the superiority of our ManiCM in terms of runtime, which verifies our intuition that incorporating the consistency model boosts the inference speed in various robotic manipulation tasks.

Comparisons on Success Rate. Table II depicts the comparison of the success of each model. The results show that our method accelerates the diffusion process without any performance drop. Specifically, with only one-step inference, our ManiCM can approximate or even surpass the state-of-the-art model DP3 and Simple DP3 by 1.3%. By distilling the diffusion process with consistency regularization, our method avoids overfitting to the training demonstrations. Especially, in the Metaworld Very Hard tasks, our

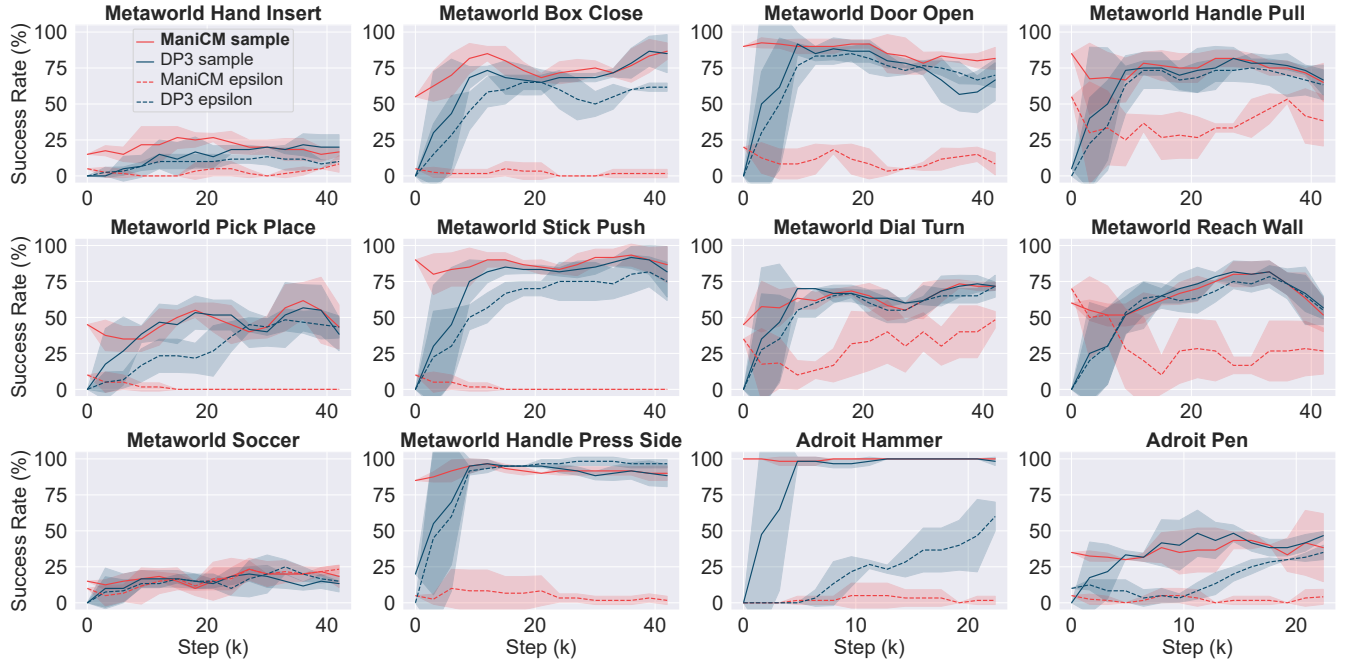


Fig. 3: **Learning Curve.** Learning curves of ManiCM with sample prediction vs. noise prediction. ManiCM converges remarkably faster by predicting action sample directly than noise.

TABLE III: **Ablation on Different Diffusion Steps of the Teacher Model.** ‘SR’ refers to the success rate. ‘ \rightarrow ’ means skipping from the original training denoising steps to k steps in inference with DDIM-Solver.

Method / DDIM Step k	Adroit		Metaworld		Average	
	Runtime	SR	Runtime	SR	Runtime	SR
DP3 (100 \rightarrow 10)	159.6	76.1	179.6	77.6	177.6	77.5
DP3 (1000 \rightarrow 50)	920.8	75.5	998.1	78.5	994.4	78.2
ManiCM (100 \rightarrow 10)	16.9	74.9	17.3	78.9	17.3	78.5
ManiCM (1000 \rightarrow 50)	19.4	77.6	16.9	75.0	17.4	75.3

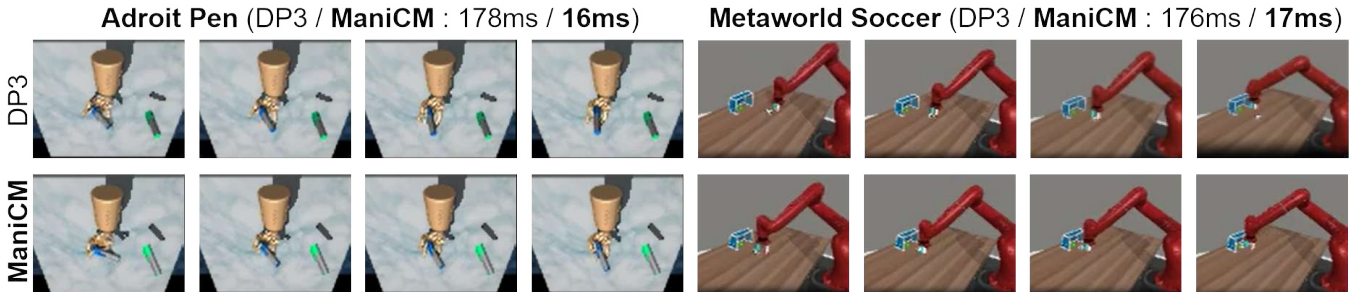


Fig. 4: **Qualitative Comparisons.** We compare ManiCM with the state-of-the-art method DP3 [6] in two typical manipulation tasks from Adroit and Metaworld, respectively. With only one-step inference, ManiCM achieves the fastest action generation while producing high-quality motions that successfully complete the tasks.

method outperforms the state-of-the-art method with an absolute improvement of 5.5%. Moreover, increasing the sampling steps in ManiCM yields even better performance on average (79.0% vs. 78.5%). The above experimental results prove the effectiveness of handling robotic tasks with our manipulation consistency model.

Comparisons on Multi-Task Setup. Figure 5 compares

ManiCM with the 3D Diffuser Actor [29] baseline on the multi-task RLbench simulation environment. The results show that ManiCM achieves competitive performance while demonstrating a remarkable 13.3 \times acceleration in inference speed, highlighting our consistency model’s effectiveness on a multi-task setup.

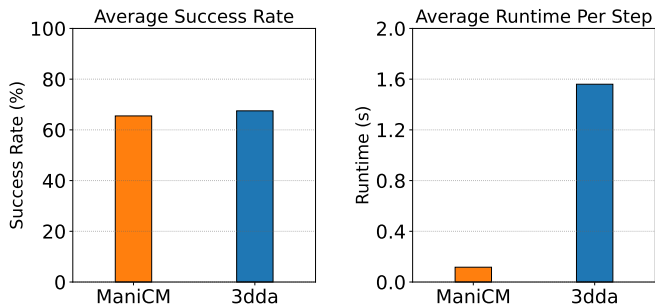


Fig. 5: **Multi-Task performance Comparison.** ManiCM balances accuracy with 3D Diffuser Actor [29] while achieving $\times 13.3$ faster inference speeds on RLbench.

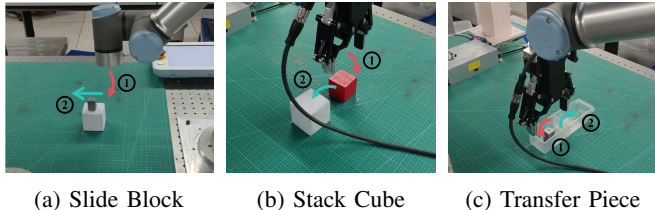


Fig. 6: **Our real-world experiment setup.** We use an end effector and a DH Robotics AG-95 gripper based on UR3e arms and include three diverse manipulation tasks. A Realsense D435i camera is applied to capture visual observations.

TABLE IV: **Real World Experiment Results.** Each task is evaluated with 10 trials.

Method	Slide Block		Stack Cube		Transfer Piece	
	SR	Runtime	SR	Runtime	SR	Runtime
DP3	90	177.2	80	181.3	70	172.4
ManiCM	80	16.9	80	17.2	80	16.8

C. Real World Experiments

As shown in Figure 6, we evaluate ManiCM in the real world on three tasks from easy to hard with different embodiments: Slide Block, Stack Cube, and Transfer Piece.

- 1) *Slide Block*: The robot has to push the gray block off the white cube with the end-effector (see Figure 6a).
- 2) *Stack Cube*: The robot has to pick up the red cube and then stack it on top of the white cube with a parallel jaw gripper (see Figure 6b).
- 3) *Transfer Piece*: The robot has to partially close the gripper, insert it into the left side of the box to pick the piece, and then place the piece on the right side of the box with a parallel jaw gripper. This task is more complex and requires higher precision (see Figure 6c).

We use an end effector and a DH Robotics AG-95 gripper based on UR3e arms and a Realsense D435i camera to capture visual observations, with an NVIDIA RTX 4090 GPU for inference. We retain the same network architecture and input-output configuration as in the simulation environment. For each task, we conduct 10 trials to evaluate the average success rate and inference time. As demonstrated in Table IV, ManiCM achieves 10 \times faster inference speeds than DP3 while maintaining comparable success rates, validating its

effectiveness in real-world setup.

D. Ablation Studies

In this section, we explore the impact of different design choices in our ManiCM.

Ablation on Sample Prediction and Epsilon Prediction. We conduct a comparison between directly predicting the sample and predicting the noise ‘epsilon’, which is a widely-used technique in the vision community [28]. From Figure 3, we can observe that sample prediction in the noise sampler brings faster convergence than predicting the noise epsilon in various tasks and methods. This is also observed in [6]. Besides, the performance of the noise prediction is even worse when we implement consistency distillation. This is because predicting the action sample is more direct than training a denoising model for the low-dimensional action manifold. More importantly, the consistency distillation process will cause compound instability, so that the performance of sample prediction is much stronger than noise prediction variation (78.5% vs. 24.4% on average).

Ablation on Different Diffusion Steps of the Teacher Model. We compare our ManiCM with the state-of-the-art method DP3 under different DDIM sampling steps in Table III. We can conclude that: 1) The task success rates do not monotonically increase when taking more diffusion sampling steps in both DP3 and ManiCM, which indicates that most of the diffusion steps are redundant. As a result, we can distill the teacher model with multiple-step inference into an online model that generates high-quality action in only one sampling step. 2) For different diffusion sampling steps, our ManiCM can stably distill competitive capacity in task completion, where it accelerates the runtime efficiency by $\sim 57 \times$ when the teacher is a DDIM with 50 inference steps.

E. Qualitative Analysis

We present two qualitative examples of the generated action sequence in Figure 4 from DP3 and our ManiCM in Adroit and MetaWorld, respectively. In the left case, the agent needs to spin the pen to a specific angle given by the green reference pen with its dexterous hand. The compared method DP3 fails to spin the pen to the correct angle, while our method succeeds in spinning it to the angle specified by the green pen on the ground. In the right case, the agent is required to kick the football into the goal with its parallel jaw gripper. DP3 stretches the gripper to the goal without holding the ball by just mimicking the expert trajectories in the training set, while ManiCM successfully kicks the ball into the goal. Both cases verify that our ManiCM accelerates the denoising process by a large margin, while maintaining the fine-grained 3D comprehension across diverse robotic tasks.

V. CONCLUSION

In this paper, we have proposed a ManiCM method that imposes the consistency constraint on the diffusion process, which brings 3D diffusion-based robotic manipulation to a real-time level. We design a manipulation consistency self-consistency function that predicts the action sample

directly based on 3D point cloud condition. Subsequently, we implement a manipulation consistency distillation to ensure the action is denoised from any point along the ODE trajectory within only one-step inference, which avoids the inefficient iterative denoising procedure in the original diffusion model. Extensive experiments across various task suites verify the effectiveness and efficiency of our method. However, the scalability of the consistency model to distill a large-scale pre-trained diffusion policy is still under-explored and we leave this issue for future work.

ACKNOWLEDGEMENT

The author team would like to acknowledge Zhixuan Liang and Yao Mu from the University of Hong Kong for their helpful technical discussion and suggestions.

REFERENCES

- [1] M. Shridhar, L. Manuelli, and D. Fox, "Cliport: What and where pathways for robotic manipulation," in *CoRL*, 2022.
- [2] S. James, K. Wada, T. Laidlow, and A. J. Davison, "Coarse-to-fine q-attention: Efficient learning for visual robotic manipulation via discretisation," in *CVPR*, 2022.
- [3] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, J. Dabis, C. Finn, K. Gopalakrishnan, K. Hausman, A. Herzog, J. Hsu, *et al.*, "Rt-1: Robotics transformer for real-world control at scale," *arXiv preprint arXiv:2212.06817*, 2022.
- [4] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, X. Chen, K. Choremanski, T. Ding, D. Driess, A. Dubey, C. Finn, *et al.*, "Rt-2: Vision-language-action models transfer web knowledge to robotic control," *arXiv preprint arXiv:2307.15818*, 2023.
- [5] C. Chi, S. Feng, Y. Du, Z. Xu, E. Cousineau, B. Burchfiel, and S. Song, "Diffusion policy: Visuomotor policy learning via action diffusion," in *RSS*, 2023.
- [6] Y. Ze, G. Zhang, K. Zhang, C. Hu, M. Wang, and H. Xu, "3d diffusion policy: Generalizable visuomotor policy learning via simple 3d representations," in *RSS*, 2024.
- [7] M. Reuss, M. Li, X. Jia, and R. Lioutikov, "Goal-conditioned imitation learning using score-based diffusion policies," 2023. [Online]. Available: <https://arxiv.org/abs/2304.02532>
- [8] M. Janner, Y. Du, J. B. Tenenbaum, and S. Levine, "Planning with diffusion for flexible behavior synthesis," in *ICML*, 2022.
- [9] A. Ajay, Y. Du, A. Gupta, J. B. Tenenbaum, T. S. Jaakkola, and P. Agrawal, "Is conditional generative modeling all you need for decision making?" in *ICLR*, 2023. [Online]. Available: <https://openreview.net/forum?id=sP1fo2K9DFG>
- [10] Z. Dong, Y. Yuan, J. Hao, F. Ni, Y. Mu, Y. Zheng, Y. Hu, T. Lv, C. Fan, and Z. Hu, "Aligndiff: Aligning diverse human preferences via behavior-customisable diffusion model," in *arXiv preprint 2310.02054*, 2023.
- [11] F. Ni, J. Hao, Y. Mu, Y. Yuan, Y. Zheng, B. Wang, and Z. Liang, "Metadiffuser: Diffusion model as conditional planner for offline meta-rl," *International Conference on Machine Learning, ICML*, 2023.
- [12] Y. Du, S. Yang, B. Dai, H. Dai, O. Nachum, J. B. Tenenbaum, D. Schuurmans, and P. Abbeel, "Learning universal policies via text-guided video generation," in *NeurIPS*, 2023.
- [13] T. Pearce, T. Rashid, A. Kanervisto, D. Bignell, M. Sun, R. Georgescu, S. V. Macua, S. Z. Tan, I. Momennejad, K. Hofmann, and S. Devlin, "Imitating human behaviour with diffusion models," in *ICLR*, 2023.
- [14] Z. Wang, J. J. Hunt, and M. Zhou, "Diffusion policies as an expressive policy class for offline reinforcement learning," in *ICLR*, 2023.
- [15] Z. Xian, N. Gkanatsios, T. Gervet, T.-W. Ke, and K. Fragkiadaki, "Chaineddiffuser: Unifying trajectory diffusion and keypose prediction for robotic manipulation," in *CoRL*, 2023.
- [16] X. Ma, S. Patidar, I. Haughton, and S. James, "Hierarchical diffusion policy for kinematics-aware multi-task robotic manipulation," *CVPR*, 2024.
- [17] G. Yan, Y.-H. Wu, and X. Wang, "Dnact: Diffusion guided multi-task 3d policy learning," *arXiv preprint arXiv:2403.04115*, 2024.
- [18] G. Lu, S. Zhang, Z. Wang, C. Liu, J. Lu, and Y. Tang, "Manigaussian: Dynamic gaussian splatting for multi-task robotic manipulation," *arXiv preprint arXiv:2403.08321*, 2024.
- [19] Y. Ze, G. Yan, Y.-H. Wu, A. Macaluso, Y. Ge, J. Ye, N. Hansen, L. E. Li, and X. Wang, "Gnfactor: Multi-task real robot learning with generalizable neural feature fields," in *CoRL*, 2023, pp. 284–301.
- [20] C. Lu, P. J. Ball, and J. Parker-Holder, "Synthetic experience replay," in *Workshop on Reincarnating Reinforcement Learning at ICLR*, 2023.
- [21] T. Yu, T. Xiao, A. Stone, J. Tompson, A. Brohan, S. Wang, J. Singh, C. Tan, D. M. J. Peralta, B. Ichter, K. Hausman, and F. Xia, "Scaling robot learning with semantically imagined experience," in *RSS*, 2023.
- [22] H. He, C. Bai, K. Xu, Z. Yang, W. Zhang, D. Wang, B. Zhao, and X. Li, "Diffusion model is an effective planner and data synthesizer for multi-task reinforcement learning," in *NeurIPS*, 2023.
- [23] A. Mandlekar, D. Xu, J. Wong, S. Nasiriany, C. Wang, R. Kulkarni, L. Fei-Fei, S. Savarese, Y. Zhu, and R. Martín-Martín, "What matters in learning from offline human demonstrations for robot manipulation," *arXiv preprint arXiv:2108.03298*, 2021.
- [24] J. Song, C. Meng, and S. Ermon, "Denoising diffusion implicit models," *arXiv preprint arXiv:2010.02502*, 2022.
- [25] Z. Dong, J. Hao, Y. Yuan, F. Ni, Y. Wang, P. Li, and Y. Zheng, "Diffuserlite: Towards real-time diffusion planning," *arXiv preprint arXiv:2401.15443*, 2024.
- [26] Y. Song, P. Dhariwal, M. Chen, and I. Sutskever, "Consistency models," in *ICML*, 2023.
- [27] S. Luo, Y. Tan, L. Huang, J. Li, and H. Zhao, "Latent consistency models: Synthesizing high-resolution images with few-step inference," *arXiv preprint arXiv:2310.04378*, 2023.
- [28] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," *NeurIPS*, pp. 6840–6851, 2020.
- [29] T.-W. Ke, N. Gkanatsios, and K. Fragkiadaki, "3d diffuser actor: Policy diffusion with 3d scene representations," *arXiv preprint arXiv:2402.10885*, 2024.
- [30] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan, and S. Ganguli, "Deep unsupervised learning using nonequilibrium thermodynamics," in *ICML*, 2015, pp. 2256–2265.
- [31] A. Q. Nichol and P. Dhariwal, "Improved denoising diffusion probabilistic models," in *ICML*, 2021, pp. 8162–8171.
- [32] R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *CVPR*, 2022, pp. 10 684–10 695.
- [33] S. Luo, Y. Tan, S. Patil, D. Gu, P. von Platen, A. Passos, L. Huang, J. Li, and H. Zhao, "Lcm-lora: A universal stable-diffusion acceleration module," *arXiv preprint arXiv:2311.05556*, 2023.
- [34] J. Chen, Y. Wu, S. Luo, E. Xie, S. Paul, P. Luo, H. Zhao, and Z. Li, "Pixart- $\{\delta\}$: Fast and controllable image generation with latent consistency models," *arXiv preprint arXiv:2401.05252*, 2024.
- [35] J. Xiao, K. Zhu, H. Zhang, Z. Liu, Y. Shen, Y. Liu, X. Fu, and Z.-J. Zha, "Ccm: Adding conditional controls to text-to-image consistency models," *arXiv preprint arXiv:2312.06971*, 2023.
- [36] X. Wang, S. Zhang, H. Zhang, Y. Liu, Y. Zhang, C. Gao, and N. Sang, "Videolcm: Video latent consistency model," *arXiv preprint arXiv:2312.09109*, 2023.
- [37] F.-Y. Wang, Z. Huang, X. Shi, W. Bian, G. Song, Y. Liu, and H. Li, "Animatelcm: Accelerating the animation of personalized diffusion models and adapters with decoupled consistency learning," *arXiv preprint arXiv:2402.00769*, 2024.
- [38] W. Dai, L.-H. Chen, J. Wang, J. Liu, B. Dai, and Y. Tang, "Motionlcm: Real-time controllable motion generation via latent consistency model," *arXiv preprint arXiv:2404.19759*, 2024.
- [39] Y. Bai, T. Dang, D. Tran, K. Koishida, and S. Sojoudi, "Accelerating diffusion-based text-to-audio generation with consistency distillation," *arXiv preprint arXiv:2309.10740*, 2023.
- [40] Y. Chen, H. Li, and D. Zhao, "Boosting continuous control with consistency policy," *arXiv preprint arXiv:2310.06343*, 2023.
- [41] A. Prasad, K. Lin, J. Wu, L. Zhou, and J. Bohg, "Consistency policy: Accelerated visuomotor policies via consistency distillation," *arXiv preprint arXiv:2405.07503*, 2024.
- [42] Z. Ding and C. Jin, "Consistency models as a rich and efficient policy class for reinforcement learning," *arXiv preprint arXiv:2309.16984*, 2023.
- [43] D. Kingma, T. Salimans, B. Poole, and J. Ho, "Variational diffusion models," *NeurIPS*, vol. 34, pp. 21 696–21 707, 2021.
- [44] T. Yu, D. Quillen, Z. He, R. Julian, A. Narayan, H. Shively, A. Bellathur, K. Hausman, C. Finn, and S. Levine, "Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning," *arXiv preprint arXiv:1910.10897*, 2021.

- [45] A. Rajeswaran, V. Kumar, A. Gupta, G. Vezzani, J. Schulman, E. Todorov, and S. Levine, "Learning complex dexterous manipulation with deep reinforcement learning and demonstrations," *arXiv preprint arXiv:1709.10087*, 2018.
- [46] Y. Seo, D. Hafner, H. Liu, F. Liu, S. James, K. Lee, and P. Abbeel, "Masked world models for visual control," in *CoRL*, 2023, pp. 1332–1344.
- [47] C. Wang, X. Luo, K. Ross, and D. Li, "Vrl3: A data-driven framework for visual deep reinforcement learning," *arXiv preprint arXiv:2202.10324*, 2023.
- [48] S. James, Z. Ma, D. R. Arrojo, and A. J. Davison, "Rlbench: The robot learning benchmark & learning environment," *RA-L*, 2020.
- [49] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," *arXiv preprint arXiv:1711.05101*, 2019.
- [50] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimeshein, L. Antiga, A. Desmaison, A. Köpf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, "Pytorch: An imperative style, high-performance deep learning library," 2019.