S²-Diffusion: Generalizing from Instance-level to Category-level Skills in Robot Manipulation

Quantao Yang[*1], Michael C. Welle[*1,2], Danica Kragic[1], and Olov Andersson[1]

Abstract— Recent advances in skill learning has propelled robot manipulation to new heights by enabling it to learn complex manipulation tasks from a practical number of demonstrations. However, these skills are often limited to the particular action, object, and environment *instances* that are shown in the training data, and have trouble transferring to other instances of the same category. In this work we present an open-vocabulary Spatial-Semantic Diffusion policy (S²-Diffusion) which enables generalization from instance-level training data to category-level, enabling skills to be transferable between instances of the same category. We show that functional aspects of skills can be captured via a promptable semantic module combined with a spatial representation. We further propose leveraging depth estimation networks to allow the use of only a single RGB camera. Our approach is evaluated and compared on a diverse number of robot manipulation tasks, both in simulation and in the real world. Our results show that S²-Diffusion is invariant to changes in category-irrelevant factors as well as enables satisfying performance on other instances within the same category, even if it was not trained on that specific instance. Full videos of all real-world experiments are available in the supplementary material.
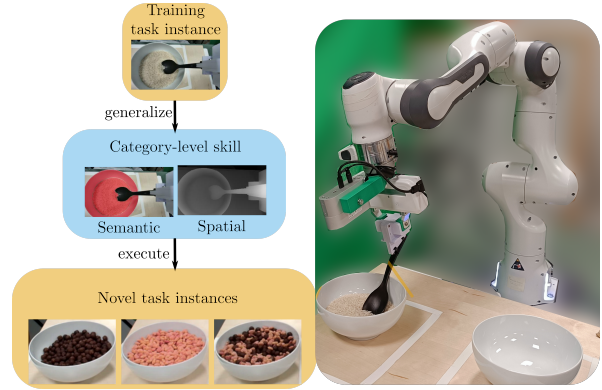
Fig. 1. Our open-vocabulary Spatial-Semantic Diffusion policy (S²-Diffusion) not only efficiently completes the task at hand but also enables the generalization of the same skill across diverse contexts and task variations. For instance, a rice-scooping policy can be directly transferred to scoop cereal without any fine-tuning.

I. INTRODUCTION

Imitation learning (IL) [1], [2] has shown potential in enabling robotic manipulation in challenging real-world scenarios by learning complex skills from human demonstrations. Still, existing IL methods often struggle to generalize beyond the specific training environments from which the demonstrations are derived. This is an important obstacle as each new environment requires labor-intensive data collection, model fine-tuning, and retraining to adapt the learned policies.

For humans, transferring knowledge between tasks and skills, such as transferring the scooping skill from rice to cereals, is rather straightforward. Scooping rice or cereals may be considered as different instances of the same task for current IL methods. The ability to generalize over such instances is still a challenge and requires rather advanced spatial-semantic understanding [3]. The ability to transfer and generalize over instances removes the necessity for extensive training and also allows for assessing what type of instances one can transfer over - for example, scooping ice cream may be very different from scooping granular material such as cereals or rice. Thus, granular materials may be seen as the same category as rice and cereals, while ice cream is an instance of another category which requires a very different policy when executing the scooping task.

Large pre-trained Visual-Language-Action (VLA) models [4], [5], [6] generalize simple skills such as pick-and-place over a wide range of environments and objects. However, more complex non-prehensile manipulation such as scooping, mug-flipping, cooking shrimp or opening a bottle with a bottle opener stay elusive for such large general models. Recent imitation learning approaches address learning of instances of challenging manipulation tasks [1], [2], [7], [8], [9], [10], [11] but the integration with semantic knowledge in highly-complex manipulation tasks remains a challenge [9]. The aforementioned methods often rely on raw perceptual features and environmental conditions, limiting their applicability to the instances observed during the training. Training a skill via imitation learning, such as a diffusion policy [9], relies on expert demonstrations that often do not cover several instances of the same task. We show that when trained only on a particular instance of a task - such as wiping red scribbles from a whiteboard - the skill fails to transfer already when the scribbles are now green, even if the required action and environment for wiping is exactly the same. This is because the policy did not learn a *whiteboard-wiping* category skill but a single instance of this category namely *red-whiteboard-wiping*.

Motivated by the above challenges, we present a novel approach that integrates spatial prediction with semantic segmentation features from large pre-trained models [12], [13] to generalize from expert demonstrations on a single

1 Division of Robotics, Perception and Learning (RPL), KTH Royal Institute of Technology, Sweden. (e-mail: quantao@kth.se).

2 INCAR Robotics AB, Sweden.

instance of a task to its *category-level skill* – such as wiping different color scribbles from the whiteboard or scooping different granular material from bowl to bowl. Our method uses a single RGB camera view combined with the proprioceptive information of the robot. As shown in Fig. 1, we extract semantic information using the prompted foundation model [14] and combine it with a depth estimation foundation model [15] to obtain *Spatial-Semantic* observations for the visuomotor diffusion policy learning framework. This allows for invariance to task-irrelevant factors such as background and object textures as well as the capability to generalize from instance-level to category-level skills. Our key contributions are threefold:

1) We propose to endow visuomotor diffusion policies with spatial-semantic understanding to enable generalization from instance-level to category-level skills in robot manipulation tasks.

2) We introduce an efficient representation of the spatial-semantic information via a combination of vision foundation models. The overall framework is real-time viable and requires only a single RGB camera and the robot's proprioceptive observations.

3) Our extensive experiments evaluate the method on a set of robotics manipulation tasks in simulation and the real world, demonstrating the ability to learn generalizable and effective robotic manipulation policies.

All real-world experimental videos (174) are available in the supplementary material.

II. RELATED WORK

A. *Visual Feature Based Imitation Learning*

In recent studies, visual imitation learning methods [16], [17], [18], [19] have shown great potential in diverse robot manipulation tasks. The recent work of Zhu et al. [3] demonstrates the potential of object-based representations for manipulation by using a conventional closed-set object detector. In [20], the authors validate that large-scale video generative pre-training is able to effectively benefit visual robot manipulation learning. However, in their works, the finetuned policy is not demonstrated to generalize to novel instances of the task. 3D vision based imitation learning [21], [22], [23], [24] has shown to improve performance but typically requires multiple posed views with RGB-D sensors to reconstruct the scene. Another work [25] also ulitizes pretrained VLMs to provide scene representation for robot tasks, but their approach needs to construct a 3D neural feature field by scanning part of the scene. In our paper, we propose a visuomotor imitation learning method that takes advantage of object-aware semantic representation to focus on task-relevant objects for training a visuomotor policy.

Recently, Wang et al. [26] introduce a novel framework that enhances generalization capabilities by incorporating explicit spatial and semantic information into policy learning. This method uses multi-view RGB-D observations to generate 3D descriptor fields and then constructs semantic fields that highlight task-relevant parts of objects (e.g., a knife handle or soda can tab). By combining 3D geometric and semantic information, this approach achieves significant improvements in generalization at the cost of requiring multiple RGB-D cameras.

B. *Vision Language Models in Robotics*

Vision-Language Models (VLMs), trained on vast amounts of internet data, have found widespread use in robotic applications [27], [28], [29]. Some works [30], [31], [32], [26] have explored leveraging 2D foundation vision models to construct open-vocabulary 3D representations. These approaches involve utilizing visual features from pretrained foundation models like CLIP [27] or SAM [33] to scene representations that benefit learning downstream robot policy. The most recent works [12], [34], [35] demonstrate superior open-vocabulary classification ability which succeed in generalizing to unseen classes. Pretrained foundation models are also utilized by either being prompted or fine-tuned to generate high-level task plans [36], [31] and to shape reward functions [37], [38], [39] for reinforcement learning. In [40], the authors introduce a multimodal diffusion transformer policy for solving long-horizon tasks. In contrast, our approach concentrates on improving generalization ability for open-vocabulary manipulation policy. MOKA [41] addresses robotic manipulation by using VLMs to mark open-world keypoint affordances. The core idea behind both MOKA and our method is similar, that is guiding the policy to focus on task-relevant objects. However, our method utilizes a more generalizable semantic representation and also depth information for the entire scene.

C. *Vision Language Actions in Robotics*

Large policies or Vision-Language Actions (VLAs), pretrained on a combination of Internet-scale data and diverse robot demonstrations, is another promising research direction for generalizable policy learning in robotics. Recent works [42], [5], [43], [44] propose to co-finetune robot trajectory data alongside vision-language data, demonstrating impressive generalization capabilities with novel objects and instructions. However, these are complex and computationally costly attempts at general manipulation that while providing encouraging results at task reasoning have so far not been able to compete with imitation-based skill learning on non-prehensile and contact-rich manipulation tasks. To enhance generalization ability, [45] further proposes a cross-embodied robot policy trained on the diverse robot dataset to control robots with varying observation and action types. For comparison, our method focuses on policy generalization across different tasks by concentrating solely on the segmentation masks of target objects.

III. TOWARDS GENERALIZABLE ROBOTIC SKILLS

We start with a question: "What does it mean for a skill to be *generalizable*?". Commonly, "mug flipping" trained on a specific mug with distinct appearance and geometry will not generalize to flipping other mugs. Instead, the learned skill remains instance-specific, as neural network-based methods

optimize the training loss without explicit interpretability of the learned features. Consequently, if these (self-selected) features are absent in another mug instance, the skill will fail to perform effectively.

One approach to mitigate this limitation is to explicitly learn features that are shared across all instances within a category. For example, a "mug" could be characterized by shared geometric features, such as a cylindrical body and a handle. Works such as ShapeNet [46] provide large-scale repositories of 3D shapes categorized into object classes, enabling methods that are able to learn category-level features that can be generalized over individual instances [47]. These approaches enable generalization across objects within the same class while preserving distinctions between categories.

This object-centric approach has proven effective for tasks involving well-categorized objects like mugs, shoes, pens, or soda cans. However, tasks like wiping or scooping present unique challenges that cannot be addressed solely by these methods. In this work, we follow a more *action*-centric approach, that considers the *semantic functionality* of the skill rather than specific object categories.

In this context, the concept of affordances [48] provides a useful lens to interpret our action-centric approach. Affordances, which describe the potential actions that an object or environment can support, emphasize functionality over rigid categorization. While our work focuses on learning lower-level skills and contact-rich tasks, which are difficult to reduce to affordances, it shares a similar philosophy by focusing on the semantic functionality of skills rather than specific object categories.

A. Functional and Semantic Abstractions

When considering robotic skills, it is essential to move beyond instance-specific implementations and emphasize a leveled abstraction of skills. This facilitates generalization across instances and categories, aligning with the notion that skills can share functional similarities despite differing in object appearances, materials, or environmental contexts. In Fig. 2 we show an example of such a skill levels - depicting the functional goals on the top, able to be achieved with different category-level skills and performed on instances of that category. As the example in Fig. 2 shows, the skill flipping represents a generic functional task: "the act of inverting an object". Within this abstraction, mug flipping is a category-level skill that applies to any object classified as a "mug". However, when trained specifically on a single mug (e.g., "a blue cylindrical mug with a narrow handle"), the skill becomes an instance-specific skill, which may not generalize to mugs with varying shapes, textures, or weights. Similarly, the skill scooping provides another illustrative example. At its core, scooping refers to the functional action of transferring a granular or semi-solid material from one location to another. Category-level skill: Bowl-to-bowl scooping captures the general action of transferring materials between two containers, encompassing a wide range of granular and semi-solid materials. Instance-level skills: Tasks such as rice scooping or cereal scooping are more specific,

Functional goal	flipping						scooping					
Category-skill	mug-flipping			food-flipping			bowl-to-bowl			pile-to-container		
Instance-skill	red-mug-flipping	⋮	blue-mug-flipping	burger-flipping	⋮	pancake-flipping	rice-bowl-to-bowl	⋮	cereal-bowl-to-bowl	sand-pile-to-container	⋮	gravel-pile-to-container

Fig. 2. Skill level example for flipping and scooping. The functional goal is stated as an abstract action on the top row, second row shows examples of category-level skills that fall under this functional similarity. The bottom row shows Instances of the respective categories.

as they have different visual appearances as well as grain size and density.

In this work, we define an instance-level skill as a skill learned from specific demonstrations that are tightly coupled to a particular object, material, or environmental setup. For example, a *rice-bowl-to-bowl scooping* policy trained exclusively on a dataset containing only rice would constitute an instance-level skill, as the robot may fail to generalize when attempting to scoop a different granular material, such as cereal or sand. On the other hand, a category-level skill is a more abstract representation of a skill that remains valid across multiple instances within a category. For example, *bowl-to-bowl scooping* encompasses a variety of granular materials, such as rice, cereal, or lentils, enabling the robot to execute the task reliably across these different instances. Category-level skills incorporate a more generalized functional understanding, allowing the robot to adapt to new but related scenarios without explicit retraining.

In practice, all training data - in the real world - will come from instance-specific setups for a category-level skill. One way to achieve generalization is simple to present the imitation learning method with a wide range of instances in order to cover the whole category and achieve generalization. This approach, however, has the drawback of being very labor-intensive and therefore costly when done in the real world. We address this shortcoming by focusing on Spatial-Semantic features that can be extracted from a single instance but are still informative enough so that generalization can happen. In other words when we learn a visuomotor diffuson policy with Spatial-Semantic observations - instead of RGB - we can generalize from instance-level to its category-level skill.

IV. PROBLEM FORMULATION

Let Ψ be the space of RGB images. Consider a manipulation task given the language instruction of the target object $\mathcal{L}$ (e.g., "coffee mug"). Our goal is to learn a generalizable imitation learning policy by leveraging spatial-semantic representation from pretrained Vision-Language models.
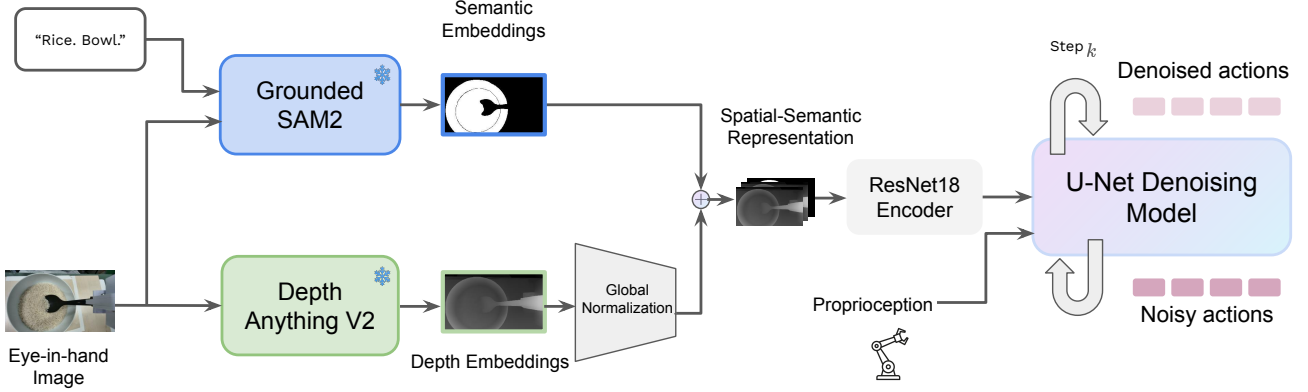
Fig. 3. **S^2-Diffusion Architecture**. The architecture is composed of three components: a pretrained semantic segmentation model *Grounded-SAM2* [14], a pretrained depth prediction model *DepthAnythingV2* [13] and a U-Net denoising diffusion policy [9]. We design an object-aware spatial-semantic representation that is leveraged for denoising probabilistic model.

We consider a robotic task as a Markov Decision Process (MDP) defined by a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{P}, r, \rho, \gamma)$ of states, actions, transition probability, reward, initial state distribution, and discount factor. We assume access to a dataset $D = \{\tau_i\}_i^N$ of N demonstrated expert trajectories $\tau_i = \{(s_0, a_0), ..., (s_{T_i}, a_{T_i})\}$ for the task. Our method uses a denoising diffusion process [9] to learn imitation policy π from D. To generalize from individual instances to unseen instances from the same category, we propose to build a spatial-semantic representation. In this paper, $\mathcal{S}$ is the state space composed of visual spatial-semantic representation f_v and robot proprioception states q. $\mathcal{A}$ is the action space of robot end-effector commands. We aim to learn a policy $\pi_\theta(a|s) : \mathcal{S} \rightarrow \mathcal{A}$ with parameters θ that predicts action a according to current state s for an MDP by leveraging the prior experience contained in the dataset D.

V. METHOD

Our objective is to develop an open-vocabulary spatial-semantic visuomotor policy that can generalize from an individual instance to other unseen instances resulting in a category-level skill. We propose open-vocabulary Spatial-Semantic Diffusion policy (S^2-Diffusion), an approach that leverages three main components in policy learning: a semantic segmentation model, a depth prediction model and a diffusion policy shown in Fig. 3. The policy is trained with demonstrations from expert teleoperation, using only RGB images and robot proprioception as the state, and end-effetor velocities as the commanded actions respectively.

A. Diffusion for Robot Skill Learning

Following previous works [9], [49], we formulate the visuomotor policy as a conditional Denoising Diffusion Probabilistic Model (DDPM) [50], [51]. Starting from random action a^K sampled from Gaussian noise, the diffusion probabilistic model ϵ_θ performs K iterations of denoising. This process gradually produces a sequence of actions with decreasing noise levels, $a^K, a^{k-1}, ..., a^0$, until the noise-free action a^0. Each action denoising iteration is described as:

$$a^{k-1} = \alpha_k(a_k - \gamma_k \epsilon_\theta(a^k, o, k)) + \sigma_k \mathcal{N}(0, I), \quad (1)$$

where o is the observation for the policy. α_k, γ_k and σ_k are referred as noise schedule for each iteration k, and $\mathcal{N}(0, I)$ is the Gaussian noise added to the action.

To learn the action predicting model π_θ, we randomly sample the robot action a^0 from the demonstration dataset D and add the noise ϵ^k for a random iteration k. The training loss for the diffusion model is formulated as:

$$\mathcal{L} = MSE(a^0, \pi_\theta(a^0 + \epsilon^k, o, k)), \quad (2)$$

where we use an action sampling approach rather than a noise prediction model to enhance the generation of high-dimensional actions.

B. Open-Vocabulary Spatial-Semantic Representation

We aim to design spatial-semantic-aware representation that is leveraged for the observation of the above denoising probabilistic model. We utilize two pretrained VLMs, *Grounded-SAM2* [14] and *DepthAnythingV2* [13], for open-vocabulary semantic segmentation and depth map estimation respectively. We use *Grounded-SAM2* model to perform zero-shot semantic segmentation, leveraging CLIP-based [27] mask classification to segment unseen classes. We combine the extracted features to construct a spatial-semantic representation that is leveraged as the input for the visuomotor diffusion policy.

We utilize *Grounded-SAM2* to segment an image into a set of semantic masks $(z_1, z_2, ..., z_n)$ from visual observations based on text descriptions. We apply pixel-wise maximum pooling for each pixel location (i, j) across all segmentation masks:

$$z_f(i, j) = \max_{s=1}^{n} z_s(i, j), \quad (3)$$

where $z_s(i, j)$ represents the pixel value at position (i, j) in the s-th mask. In this way, we combine multiple segmentation masks into a single mask z_f where each pixel represents the most confident prediction from the set of masks.

Algorithm 1: Learning Open-Vocabulary Spatial-Semantic Diffusion Policy

---

Input : Semantic query l, image observation o_t, robot state q, *Grounded-SAM2* model C_1, *DepthAnythingV2* model C_2

1 Collect demonstrated trajectories $D = \{\tau_i\}_i^N$
2 **for** *epoch n=1,N* **do**
3 $\quad$ Sample raw image o_t and robot action a^0
4 $\quad$ Obtain spatial-semantic representation
5 $\quad\quad$ $z_s = C_1(o_t, l), \ z_d = C_2(o_t)$
6 $\quad\quad$ $z_f(i, j) = \max_{s=1}^n z_s(i, j)$
7 $\quad\quad$ $f_v = \text{ResNet}(z_f \| z_d)$
8 $\quad$ Add Gaussian noise $\epsilon^k \sim \mathcal{N}(0, I)$ for step k
9 $\quad\quad$ $a^k = a^0 + \epsilon^k$
10 $\quad$ Train the policy
11 $\quad\quad$ $\mathcal{L} = MSE(a^0, \pi_\theta(a^k, k, f_v, q))$
12 **end**
13 **return** the trained policy $\pi_\theta(a_t | o_t, q, k)$

To improve the spatial reasoning of the imitation policy, we propose to incorporate depth map of the task space into its semantic representation. Specifically, the input image is also processed separately with a pretrained 335M-parameter *DepthAnythingV2* model [13] that shows promising performance in fine-grained details. The Depth-Anything model predicts depth estimates relative to the input RGB observations rather than absolute values. This can result in inconsistencies and inaccuracies over extended tasks or manipulation horizons. To address this, we normalize the depth maps during both training and evaluation, ensuring consistency across diverse scenes and improving the model's robustness and reliability.

The resulting semantic and spatial feature vectors are concatenated along the channel dimension to form the spatial-semantic representation. Upon generating the spatial-semantic representation, we leverage it as input for a visuomotor diffusion policy [9].

C. Learning Semantic Diffusion Policy

To effectively utilize our open-vocabulary spatial-semantic representations, we adopt the CNN-based diffusion policy architecture [9] as our decision-making backbone. We use Denoising Diffusion Implicit Models (DDIM) [53] as the noise scheduler. In our paper, we denote the observation with s_t that is composed of spatial-semantic feature f_v and robot proprioceptive state q. The training loss in Equation 2 is defined as:

$$\mathcal{L} = MSE(a^0, \pi_\theta(\alpha_k a^0 + \beta_k \epsilon^k, k, f_v, q)), \quad (4)$$

where α_k and β_k are used for noise schedule of each step. The learning process for our S^2-Diffusion method is described in Algorithm 1. We combine features inferred by VLMs *Grounded-SAM2* and *DepthAnythingV2* to construct the spatial-semantic representation for the action denoising model. By conditioning on the tuple (a^k, k, f_v, q), the denoising model learns to predict the clean action by using mean square error loss for action supervision.

VI. EVALUATION

The goals of all our experiments are three-fold:
1) to evaluate and compare the performance of our method on challenging robotic manipulation tasks;
2) to validate that generalization from instance-level to category-level skill is achieved in a real-world setting;
3) to perform ablations in order to investigate the role of the semantic and spatial components.

We first describe the experiments performed in the simulation, followed by the experiments on physical hardware.

A. Simulation Experiments

Experiment Setup. For our simulation experiments, we take advantage of a recent open-sourced large-scale simulation environment, *RoboCasa* [52], which provides expert demonstrations for diverse everyday tasks. We evaluate our method and the baselines in a set of single-stage tasks as shown in Fig. 4: *ServeMug*, *CloseDoor*, *TurnOnMicrowave*, *TurnOffFaucet*, *MoveSoda* using the provided 50 expert demonstrations from *RoboCasa*.

Baselines. We compare our method with three baseline methods in simulation: 1) **BC-RNN**: a behavior cloning method with recurrent neural network implementation; 2) **BC-Transformer**: a behavior cloning imitation learning method with transformer architecture as the policy implementation [54]; 3) **Diffusion Policy**: the image-based diffusion policy of [9]. For real-world experiments, we compare our method against the diffusion policy. In all our experiments, we train for 500 epochs on an NVIDIA RTX 4090 GPU. We use a batch size of 64 and a learning rate of $1e-4$.

Simulation Results. We take advantage of the open-sourced implementation for the baseline methods from *RoboMimic* [54]. In the demonstration datasets for each task, we assume **variations** set by *RoboCasa* in the color and shape of the target object, as well as differences in the background environment. To test the performance of our method and the baselines, we evaluate 50 trials for each task and the corresponding success rates are listed in Table I, demonstrating the superior performance of the proposed S^2-Diffusion approach.

Due to the challenging variations in target object and background seen within the *RoboCasa* dataset, classical imitation learning policies struggle to solve the specific single-stage manipulation task. While the baseline methods—BC-RNN, BC-Transformer, and Diffusion Policy—show relatively poor performance, particularly on tasks like ServeMug, Close-Door, and MoveSoda, S^2-Diffusion consistently achieves the highest success rates. For instance, S^2-Diffusion outperforms the other methods with a success rate of 0.72 on ServeMug

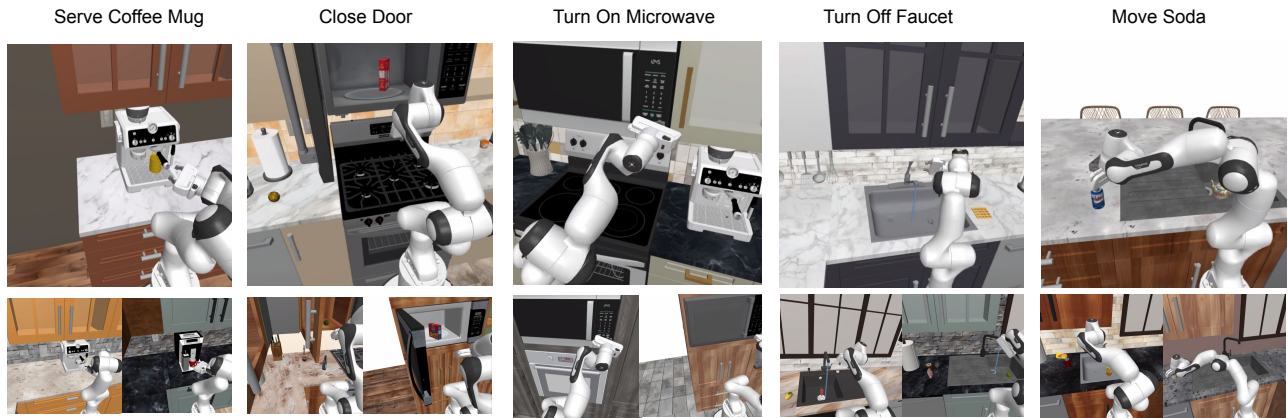| Serve Coffee Mug | Close Door | Turn On Microwave | Turn Off Faucet | Move Soda |

Fig. 4. **Simulated Tasks**. We perform evaluations on five single-stage tasks from a large-scale simulation framework RoboCasa [52]: *ServeMug*, *CloseDoor*, *TurnOnMicrowave*, *TurnOffFaucet*, *MoveSoda*. RoboCasa provides 50 expert demonstrations for each of the manipulation tasks. In the demonstration datasets for each task, we assume variations in the color and shape of the target object, as well as differences in the background environment.

TABLE I

SUCCESS RATE OF SIMULATION EXPERIMENTS

Method	Tasks				
	ServeMug	CloseDoor	TurnOnMicrowave	TurnOffFaucet	MoveSoda
BC-RNN	0.00	0.02	0.00	0.26	0.02
BC-Transformer	0.14	0.58	0.78	0.26	0.08
Diffusion Policy	0.12	0.42	0.34	0.32	0.16
S^2-Diffusion (Ours)	**0.72**	**0.78**	**0.84**	**0.70**	**0.82**

and 0.78 on CloseDoor, while the best-performing baseline, BC-Transformer, achieves only 0.14 and 0.58, respectively. On other tasks like TurnOnMicrowave and MoveSoda, S^2-Diffusion maintains a strong performance with success rates of 0.84 and 0.82. These results highlight the effectiveness of S^2-Diffusion in improving task success across a diverse range of manipulation tasks. Similar to findings in *RoboCasa* [52], the image-based Diffusion Policy is sensitive to in object color and background. In contrast, by leveraging spatial-semantic features our method shows better robustness and generality compared to state-of-the-art alternatives. We attribute this to the rich visual representation of combining semantic information and depth estimation for the workspace scene.

B. Real-World Experiments

Experiment setup. We evaluate our S^2-Diffusion method on two real-world category tasks: *whiteboard-wiping* and *bowl-to-bowl scooping*. We collected 40 and 60 expert demonstrations for the red-whiteboard-wiping and rice-bowl-to-bowl scooping tasks instances respectively. The demonstrations were obtained by teleoperating a 7-DOF Franka Panda manipulator using the Quest2ROS [55] Oculus app. A single camera providing RGB observation was mounted on the end-effector as well as task-specific tools - such as a sponge for the whiteboard wiping and a spoon for the scooping task. The teleoperation setup is shown in Fig. 5. The language prompts for obtaining the semantic observations were *"handwriting. sponge."* for the whiteboard wiping task and *"rice. bowl."*
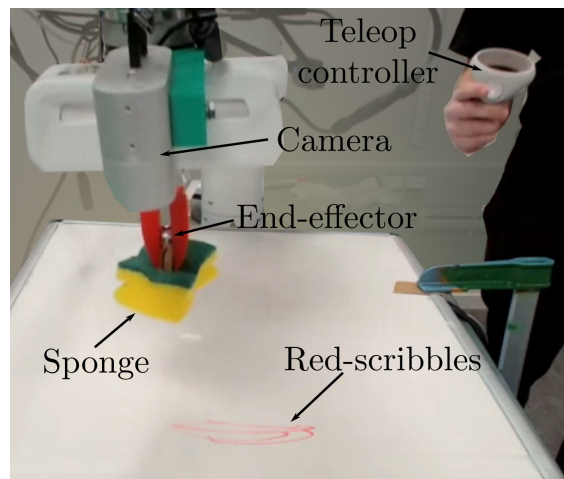

Fig. 5. Real-world setup for the wiping task showing the teleoperation controller held by the operator on the right.

for the bowl-to-bowl scooping task.

Baselines and Ablations. We compare our S^2-Diffusion method with the visuomotor diffusion method from [9] which uses RGB and proprioceptive information as a baseline, as well as perform a number of ablations on the scooping task - namely a version of our method that only has access to semantic observations (Semantic-Diffusion) and one that only observes the spatial observations (Spatial-Diffusion).

Real-World Results. The real-world experimental results are reported in Fig. 6. We evaluate our method and the baseline
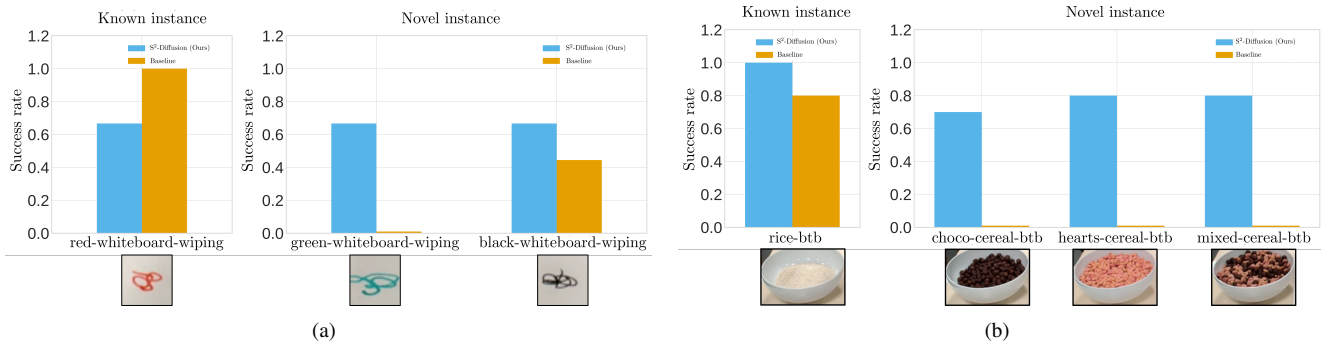
Fig. 6. Comparison of our S^2-Diffusion and the baseline on two real-world environments: whiteboard wiping and bowl-to-bowl scooping. S^2-Diffusion and the baseline are trained on *red-whiteboard-wiping* dataset and *rice-bowl-to-bowl-scooping* dataset respectively, then evaluated on the known instances and transferred to unseen instances of the two tasks. Note that for *choco-cereal-btb-scooping*, *hearts-cereal-btb-scooping*, *mixed-cereal-btb-scooping*, and *green-whiteboard-wiping* the baseline diffusion policy shows 0% success rate.

first on the seen environment (red-whiteboard-wiping and rice-bowl-to-bowl-scooping) and evaluate the transferability on other instances of the same category - namely black-whiteboard- and green-whiteboard-wiping and choco-cereal-, hearts-cereal-, mixed-cereal-bowl-to-bowl-scooping.

Whiteboard-wiping: The task involves wiping scribbles of different colors (red, black, green) from a whiteboard using the end-effector-mounted wet sponge. The results are shown in Fig. 6(a). We define success as the robot completely removing the targeted handwriting using a sponge within 15 seconds. For the task instances that are covered by the training data (red-whiteboard-wiping), the baseline is able to succeed in all nine trials, leading to a 100% success rate, however, once the policy is deployed on different instances of the task such as black-whiteboard-wiping the performance deteriorates to 4/9 (44%) and for the green-whiteboard-wiping task even to 0%.

This clearly shows how even small changes in the RGB observations such as changing the color of the scribbles can lead to great deterioration and even complete failure of the skill on this instance - underscoring that the skill learning was indeed on the instance-level and **not** category-level. On the other hand, our S^2-Diffusion method has consistent performances across all tasks. These results highlight the ability of our S^2-Diffusion to learn category-level skills for handling novel tasks without requiring additional training or fine-tuning, a capability that is essential for real-world robotic applications.

Bowl-to-bowl-scooping: The scooping task is to scoop granular materials from one bowl to another. The amount of material successfully scooped into the target bowl is measured in grams. Task success is defined as the policy's ability to scoop at least 3 grams of material into the target bowl in under 30 seconds. In Fig. 6(b) the success rates are reported over 10 trials. All real-world experimental videos are available on the project website.

For the in-distribution rice-bowl-to-bowl-scooping task, our S^2-Diffusion and baseline achieve success rates of 1.0 and 0.8, respectively. However, when transferring the policy to three unseen tasks——choco-cereal-btb-scooping, hearts-cereal-btb-scooping, and mixed-cereal-btb-scooping——the baseline diffusion policy fails entirely, with 0.0 success rate, while our S^2-Diffusion policy maintains a high success rate of approximately 0.8 by changing the semantic prompt to *"cereal. bowl."* for all three instances. This demonstrates that our method effectively generalizes from individual instances to unseen other instances of the same category.

We can see frames of the baseline diffusion policy and our method in Fig. 7, where the baseline can only succeed on the instance-level task it was trained on and fails to scoop out cereal as the visual observations are too different. Our method on the other hand extracts the semantic mask from the prompt as well as the spatial information via the synthetic depth observation. This leads to the successful execution of the scooping task and to the learning of a successful category-level skill trained on individual instances only using a single RGB observation (same as the baseline) as the original input.

C. Ablation Evaluation

To investigate the significance of integrating spatial-semantic representation, we conduct additional experiments by training the policy using only the semantic representation (Semantic-Diffusion) and only the depth map estimation (Spatial-Diffusion) on the rice and mixed-cereal-bowl-to-bowl-scooping tasks. The results of these experiments are presented in Fig. 8. The full model S^2-Diffusion, which integrates both modalities, achieves the highest success rates, significantly outperforming the ablated versions both on the seen task and also the novel task.

When the depth information is excluded, the performance of the policy drops drastically, with success rates falling to 0.4 and 0.5 for the seen and novel tasks, respectively. This significant decline underscores the critical role that spatial information plays in successfully executing 3D tasks. In contrast, when the mask (semantic representation) is removed, the performance also declines but to a lesser extent compared to the removal of depth information. While the policy's ability to generalize across tasks is still reasonable in this case, it clearly benefits from the combined use of both modalities.
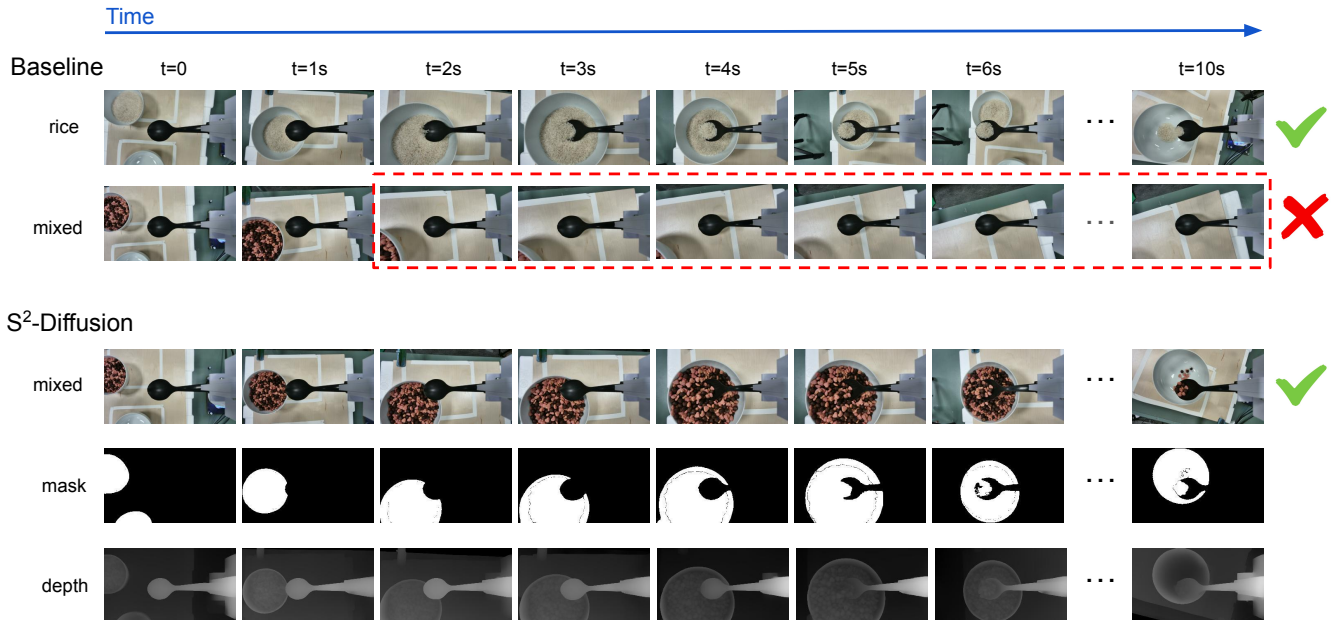
Fig. 7. Frames of the baseline diffusion policy and our S²-Diffusion method for real-world scooping tasks. We show the corresponding semantic mask and synthetic depth for each frame. The baseline can only succeed on the instance-level task it was trained on. Our method succeeds in learning a category-level skill trained on individual instances only using a single RGB observation.
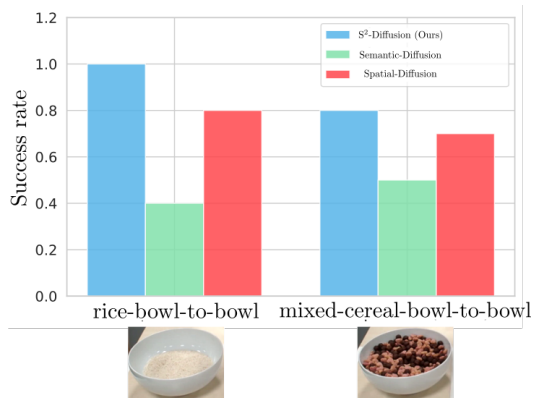

Fig. 8. Ablation study of Semantic and Spatial-diffusion only on a seen task instance (**left**) and an unseen task instance (**right**). We show how the semantic component and spatial component contribute to the performance of the policy. S²-Diffusion outperforms models trained with only semantic or spatial observations.

From these results, we conclude that both semantic representation and depth estimation are indispensable for learning a generalizable skill trained on individual instances. The integration of spatial-semantic features enhances the robustness of the policy, enabling better performance across both familiar and novel environments, and ultimately leading to more effective task execution in 3D spaces.

VII. LIMITATIONS

As Fig. 2 shows, the functional goal of *flipping* or *scooping* is discretized in different category-level skills such as *bowl-to-bowl* and *pile-to-container* scooping. While our method

does generalize from instance-level tasks to category-level tasks, in its current form it is not able to generalize well from one instance-level skill to an instance of a different category task. i.e. when only training on *rice-bowl-to-bowl* the performance will degrade on a *sand-pile-to-container* task.

While Fig. 2 makes the ordering of skills into instance and category levels look straightforward, there are some corner cases that would need to be addressed if this view was expanded into a more complex ontology. For one, the functional goal can depend on more context than what is shown in our example. For instance, *flipping* is presented in our example as a way to turn over an object, but it could also be interpreted as an action the robot should perform with its own body. Furthermore, given how current learning-from-demonstration techniques are implemented, the category *bowl-to-bowl scooping* might require additional qualifiers to accurately encompass the correct instances. For example, if we were to generalize this skill to *ice cream bowl-to-bowl scooping*, the policy would fail, as the forces required are completely different from those observed in the training instances. Ice cream, especially when frozen, requires significantly more force to be scooped in the first place. However, as the ice cream begins to melt, and the required forces become more similar to those seen during training, there is a point at which our category skill *bowl-to-bowl scooping* would likely work. We leave exploring such nuances to future work.

Another limitation of our work is its dependency on the performance of pre-trained vision foundation models. Naturally if the semantic or spatial estimate is poor, the resulting

category-level skill may generalize poorly. To address this, we plan to investigate fine-tuning VLMs in conjunction with the downstream robot policy network in future research.

VIII. CONCLUSION

In this work, we have introduced S^2-Diffusion, an open-vocabulary spatial-semantic diffusion policy that enables generalization from instance-level training data to category-level skills in robotic manipulation. Our method integrates semantic understanding with spatial representations, leveraging vision foundation models to learn a policy that is invariant to task-irrelevant visual changes and generalizes across different instances of the same category. This allows robots to transfer learned skills beyond their training data without requiring additional fine-tuning or retraining.

Through extensive simulations and real-world evaluations, we demonstrated that S^2-Diffusion outperforms the baselines. In particular we showed that:

- Spatial-Semantic representations enhance generalization – By combining spatial information with semantic segmentation, our method enables robots to focus on task-relevant features, improving instance-to-category transfer.
- Efficient real-time execution using only a single RGB camera – Unlike approaches that require multi-view setups or additional depth sensors, S^2-Diffusion extracts meaningful scene representations from a single RGB image, making it practical for real-world deployment.
- Category-level generalization – Our evaluations on a number of robotic manipulation tasks, including real-world wiping and scooping, demonstrate that the method successfully generalizes across unseen instances within the same category, achieving high performance where baseline policies fail.

In summary, S^2-Diffusion policies are less constrained by their training distribution and constitute a step toward the ability of humans to generalize skills across variations in objects, materials, and environments instances.

REFERENCES

[1] A. Mandlekar, F. Ramos, B. Boots, S. Savarese, L. Fei-Fei, A. Garg, and D. Fox, "Iris: Implicit reinforcement without interaction at scale for learning control from offline robot manipulation data," in *2020 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2020, pp. 4414–4420.

[2] A. Mandlekar, D. Xu, R. Martín-Martín, S. Savarese, and L. Fei-Fei, "Learning to generalize across long-horizon tasks from human demonstrations," in *Proceedings of Robotics: Science and Systems (RSS)*, 2020.

[3] Y. Zhu, A. Joshi, P. Stone, and Y. Zhu, "Viola: Imitation learning for vision-based manipulation with object proposal priors," in *Conference on Robot Learning*. PMLR, 2023, pp. 1199–1210.

[4] A. O'Neill, A. Rehman, A. Gupta, A. Maddukuri, A. Gupta, A. Padalkar, A. Lee, A. Pooley, A. Gupta, A. Mandlekar, *et al.*, "Open x-embodiment: Robotic learning datasets and rt-x models," *arXiv preprint arXiv:2310.08864*, 2023.

[5] O. M. Team, D. Ghosh, H. Walke, K. Pertsch, K. Black, O. Mees, S. Dasari, J. Hejna, T. Kreiman, C. Xu, *et al.*, "Octo: An open-source generalist robot policy," *arXiv preprint arXiv:2405.12213*, 2024.

[6] J. Wen, Y. Zhu, J. Li, M. Zhu, K. Wu, Z. Xu, N. Liu, R. Cheng, C. Shen, Y. Peng, *et al.*, "Tinyvla: Towards fast, data-efficient vision-language-action models for robotic manipulation," *arXiv preprint arXiv:2409.12514*, 2024.

[7] T. Z. Zhao, V. Kumar, S. Levine, and C. Finn, "Learning fine-grained bimanual manipulation with low-cost hardware," *arXiv preprint arXiv:2304.13705*, 2023.

[8] T. Gao, S. Nasiriany, H. Liu, Q. Yang, and Y. Zhu, "Prime: Scaffolding manipulation tasks with behavior primitives for data-efficient imitation learning," *IEEE Robotics and Automation Letters (RA-L)*, 2024.

[9] C. Chi, S. Feng, Y. Du, Z. Xu, E. Cousineau, B. Burchfiel, and S. Song, "Diffusion policy: Visuomotor policy learning via action diffusion," in *Proceedings of Robotics: Science and Systems (RSS)*, 2023.

[10] N. Ingelhag, J. Munkeby, J. van Haastregt, A. Varava, M. C. Welle, and D. Kragic, "A robotic skill learning system built upon diffusion policies and foundation models," *arXiv preprint arXiv:2403.16730*, 2024.

[11] Z. Fu, T. Z. Zhao, and C. Finn, "Mobile aloha: Learning bimanual mobile manipulation with low-cost whole-body teleoperation," in *arXiv*, 2024.

[12] F. Liang, B. Wu, X. Dai, K. Li, Y. Zhao, H. Zhang, P. Zhang, P. Vajda, and D. Marculescu, "Open-vocabulary semantic segmentation with mask-adapted clip," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 7061–7070.

[13] L. Yang, B. Kang, Z. Huang, X. Xu, J. Feng, and H. Zhao, "Depth anything: Unleashing the power of large-scale unlabeled data," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2024, pp. 10 371–10 381.

[14] T. Ren, S. Liu, A. Zeng, J. Lin, K. Li, H. Cao, J. Chen, X. Huang, Y. Chen, F. Yan, *et al.*, "Grounded sam: Assembling open-world models for diverse visual tasks," *arXiv preprint arXiv:2401.14159*, 2024.

[15] L. Yang, B. Kang, Z. Huang, Z. Zhao, X. Xu, J. Feng, and H. Zhao, "Depth anything v2," *arXiv preprint arXiv:2406.09414*, 2024.

[16] E. Jang, A. Irpan, M. Khansari, D. Kappler, F. Ebert, C. Lynch, S. Levine, and C. Finn, "Bc-z: Zero-shot task generalization with robotic imitation learning," in *Conference on Robot Learning*. PMLR, 2022, pp. 991–1002.

[17] O. Mees, L. Hermann, and W. Burgard, "What matters in language conditioned robotic imitation learning over unstructured data," *IEEE Robotics and Automation Letters*, vol. 7, no. 4, pp. 11 205–11 212, 2022.

[18] Z. Xian, N. Gkanatsios, T. Gervet, T.-W. Ke, and K. Fragkiadaki, "Chaineddiffuser: Unifying trajectory diffusion and keypose prediction for robotic manipulation," in *7th Annual Conference on Robot Learning*, 2023.

[19] H. Ha, P. Florence, and S. Song, "Scaling up and distilling down: Language-guided robot skill acquisition," in *Conference on Robot Learning*. PMLR, 2023, pp. 3766–3777.

[20] H. Wu, Y. Jing, C. Cheang, G. Chen, J. Xu, X. Li, M. Liu, H. Li, and T. Kong, "Unleashing large-scale video generative pre-training for visual robot manipulation," *arXiv preprint arXiv:2312.13139*, 2023.

[21] T.-W. Ke, N. Gkanatsios, and K. Fragkiadaki, "3d diffuser actor: Policy diffusion with 3d scene representations," *arXiv preprint arXiv:2402.10885*, 2024.

[22] M. Shridhar, L. Manuelli, and D. Fox, "Perceiver-actor: A multi-task transformer for robotic manipulation," in *Conference on Robot Learning*. PMLR, 2023, pp. 785–799.

[23] T. Gervet, Z. Xian, N. Gkanatsios, and K. Fragkiadaki, "Act3d: Infinite resolution action detection transformer for robotic manipulation," *arXiv preprint arXiv:2306.17817*, 2023.

[24] W. Shen, G. Yang, A. Yu, J. Wong, L. P. Kaelbling, and P. Isola, "Distilled feature fields enable few-shot language-guided manipulation," *arXiv preprint arXiv:2308.07931*, 2023.

[25] R.-Z. Qiu, Y. Hu, G. Yang, Y. Song, Y. Fu, J. Ye, J. Mu, R. Yang, N. Atanasov, S. Scherer, *et al.*, "Learning generalizable feature fields for mobile manipulation," *arXiv preprint arXiv:2403.07563*, 2024.

[26] Y. Wang, G. Yin, B. Huang, T. Kelestemur, J. Wang, and Y. Li, "Gendp: 3d semantic fields for category-level generalizable diffusion policy," in *8th Annual Conference on Robot Learning*, vol. 2, 2024.

[27] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, *et al.*, "Learning transferable visual models from natural language supervision," in *International conference on machine learning*. PMLR, 2021, pp. 8748–8763.

[28] D. Shah, B. Osiński, S. Levine, *et al.*, "Lm-nav: Robotic navigation with large pre-trained models of language, vision, and action," in *Conference on robot learning*. PMLR, 2023, pp. 492–504.

[29] J. Shang, K. Schmeckpeper, B. B. May, M. V. Minniti, T. Kelestemur, D. Watkins, and L. Herlant, "Theia: Distilling diverse vision foundation models for robot learning," *arXiv preprint arXiv:2407.20179*, 2024.

[30] P. Liu, Y. Orru, C. Paxton, N. M. M. Shafiullah, and L. Pinto, "Okrobot: What really matters in integrating open-knowledge models for robotics," *arXiv preprint arXiv:2401.12202*, 2024.

[31] B. Chen, F. Xia, B. Ichter, K. Rao, K. Gopalakrishnan, M. S. Ryoo, A. Stone, and D. Kappler, "Open-vocabulary queryable scene representations for real world planning," in *2023 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2023, pp. 11 509–11 522.

[32] C. Hao, K. Lin, S. Luo, and H. Soh, "Language-guided manipulation with diffusion policies and constrained inpainting," *arXiv preprint arXiv:2406.09767*, 2024.

[33] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A. C. Berg, W.-Y. Lo, *et al.*, "Segment anything," in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2023, pp. 4015–4026.

[34] X. Zou, J. Yang, H. Zhang, F. Li, L. Li, J. Wang, L. Wang, J. Gao, and Y. J. Lee, "Segment everything everywhere all at once," *Advances in Neural Information Processing Systems*, vol. 36, 2024.

[35] M. Oquab, T. Darcet, T. Moutakanni, H. V. Vo, M. Szafraniec, V. Khalidov, P. Fernandez, D. HAZIZA, F. Massa, A. El-Nouby, M. Assran, N. Ballas, W. Galuba, R. Howes, P.-Y. Huang, S.-W. Li, I. Misra, M. Rabbat, V. Sharma, G. Synnaeve, H. Xu, H. Jegou, J. Mairal, P. Labatut, A. Joulin, and P. Bojanowski, "DINOv2: Learning robust visual features without supervision," *Transactions on Machine Learning Research*, 2024. [Online]. Available: https://openreview.net/forum?id=a68SUt6zFt

[36] M. Ahn, A. Brohan, N. Brown, Y. Chebotar, O. Cortes, B. David, C. Finn, C. Fu, K. Gopalakrishnan, K. Hausman, *et al.*, "Do as i can, not as i say: Grounding language in robotic affordances," *arXiv preprint arXiv:2204.01691*, 2022.

[37] Y. J. Ma, W. Liang, G. Wang, D.-A. Huang, O. Bastani, D. Jayaraman, Y. Zhu, L. Fan, and A. Anandkumar, "Eureka: Human-level reward design via coding large language models," *arXiv preprint arXiv:2310.12931*, 2023.

[38] Y. J. Ma, W. Liang, H.-J. Wang, S. Wang, Y. Zhu, L. Fan, O. Bastani, and D. Jayaraman, "Dreureka: Language model guided sim-to-real transfer," *arXiv preprint arXiv:2406.01967*, 2024.

[39] P. Mahmoudieh, D. Pathak, and T. Darrell, "Zero-shot reward specification via grounded natural language," in *International Conference on Machine Learning*. PMLR, 2022, pp. 14 743–14 752.

[40] M. Reuss, Ö. E. Yağmurlu, F. Wenzel, and R. Lioutikov, "Multimodal diffusion transformer: Learning versatile behavior from multimodal goals," in *Robotics: Science and Systems*, 2024.

[41] F. Liu, K. Fang, P. Abbeel, and S. Levine, "Moka: Open-vocabulary robotic manipulation through mark-based visual prompting," *arXiv preprint arXiv:2403.03174*, 2024.

[42] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, X. Chen, K. Choromanski, 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.

[43] M. J. Kim, K. Pertsch, S. Karamcheti, T. Xiao, A. Balakrishna, S. Nair, R. Rafailov, E. Foster, G. Lam, P. Sanketi, *et al.*, "Openvla: An open-source vision-language-action model," *arXiv preprint arXiv:2406.09246*, 2024.

[44] H. Zhen, X. Qiu, P. Chen, J. Yang, X. Yan, Y. Du, Y. Hong, and C. Gan, "3d-vla: A 3d vision-language-action generative world model," *arXiv preprint arXiv:2403.09631*, 2024.

[45] R. Doshi, H. Walke, O. Mees, S. Dasari, and S. Levine, "Scaling cross-embodied learning: One policy for manipulation, navigation, locomotion and aviation," *arXiv preprint arXiv:2408.11812*, 2024.

[46] A. X. Chang, T. Funkhouser, L. Guibas, P. Hanrahan, Q. Huang, Z. Li, S. Savarese, M. Savva, S. Song, H. Su, *et al.*, "Shapenet: An information-rich 3d model repository," *arXiv preprint arXiv:1512.03012*, 2015.

[47] H. Geng, H. Xu, C. Zhao, C. Xu, L. Yi, S. Huang, and H. Wang, "Gapartnet: Cross-category domain-generalizable object perception and manipulation via generalizable and actionable parts," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2023, pp. 7081–7091.

[48] M. Lopes, F. S. Melo, and L. Montesano, "Affordance-based imitation learning in robots," in *2007 IEEE/RSJ international conference on intelligent robots and systems*. IEEE, 2007, pp. 1015–1021.

[49] 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 *Proceedings of Robotics: Science and Systems (RSS)*, 2024.

[50] J. Ho, A. Jain, and P. Abbeel, "Denoising diffusion probabilistic models," *Advances in neural information processing systems*, vol. 33, pp. 6840–6851, 2020.

[51] T. Pearce, T. Rashid, A. Kanervisto, D. Bignell, M. Sun, R. Georgescu, S. V. Macua, S. Z. Tan, I. Momennejad, K. Hofmann, *et al.*, "Imitating human behaviour with diffusion models," *arXiv preprint arXiv:2301.10677*, 2023.

[52] S. Nasiriany, A. Maddukuri, L. Zhang, A. Parikh, A. Lo, A. Joshi, A. Mandlekar, and Y. Zhu, "Robocasa: Large-scale simulation of everyday tasks for generalist robots," in *Robotics: Science and Systems (RSS)*, 2024.

[53] J. Song, C. Meng, and S. Ermon, "Denoising diffusion implicit models," *arXiv preprint arXiv:2010.02502*, 2020.

[54] 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.

[55] M. C. Welle, N. Ingelhag, M. Lippi, M. Wozniak, A. Gasparri, and D. Kragic, "Quest2ros: An app to facilitate teleoperating robots," in *7th International Workshop on Virtual, Augmented, and Mixed-Reality for Human-Robot Interactions*, 2024.