Learning 3D Dynamic Scene Representations for Robot Manipulation

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Abstract: 3D scene representation for robot manipulation should capture three key object properties: permanency – objects that become occluded over time continue to exist; amodal completeness – objects have 3D occupancy, even if only partial observations are available; spatiotemporal continuity – the movement of each object is continuous over space and time. In this paper, we introduce 3D Dynamic Scene Representation (DSR), a 3D volumetric scene representation that simultaneously discovers, tracks, reconstructs objects, and predicts their dynamics while capturing all three properties. We further propose DSR-Net, which learns to aggregate visual observations over multiple interactions to gradually build and refine DSR. Our model achieves state-of-the-art performance in modeling 3D scene dynamics with DSR on both simulated and real data. Combined with model predictive control, DSR-Net enables accurate planning in downstream robotic manipulation tasks such as planar pushing. Please find additional results and videos in the supplementary material. Code and data are available at https://dsr-net.cs.columbia.edu.

Keywords: Predictive Model, Manipulation, 3D Vision

1 Introduction

Our physical world is three-dimensional, where the full extent of objects – their shape and motion – exists and persists in 3D space. Despite this, the vast majority of visual predictive models currently used in robotics, which predict the motion of objects under the effect of an applied action, remain limited to only predicting 2D motion (i.e. optical flow) of partial observations, e.g. predicting the 2D flow of pixels [1, 2], or predicting the 3D scene flow of visible points from a partial point cloud [3, 4]. Unfortunately, modeling the motion of only visible surfaces often leads to data degeneration, where objects fade and vanish from the representation as they become occluded. This causes the predictive models to perform poorly in cluttered environments, in which objects frequently appear, disappear, then reappear in view as the robot move them around.

In this work, we investigate the benefits of learning a complete and persistent 3D scene representation for visual predictive modeling. We present **3D Dynamic Scene Representation (DSR)**: a 3D volumetric scene representation that simultaneously discovers, tracks and reconstructs novel objects and predicts their motion under a robot's interactions. Specifically, the representation captures three object properties, all of which have long been argued as crucial to human scene understanding [5].

- **Permanence:** visual information is aggregated into a persistent 3D representation. This means that as objects disappear from view due to occlusion, they remain in the representation. This enables more accurate predictions of object motion when it is moved by other objects in occlusion, or when it gradually reappears in view.
- **Amodal completeness:** from partial observations of the scene, DSR infers complete 3D occupancy of each object, including regions that are not directly observed. This attribute enables it to predict the rigid body motion of the entire object instead of only visible surfaces.
- **Spatiotemporal continuity:** the representation recognizes individual object instances and tracks their identity over time.

∗ Indicates equal contribution

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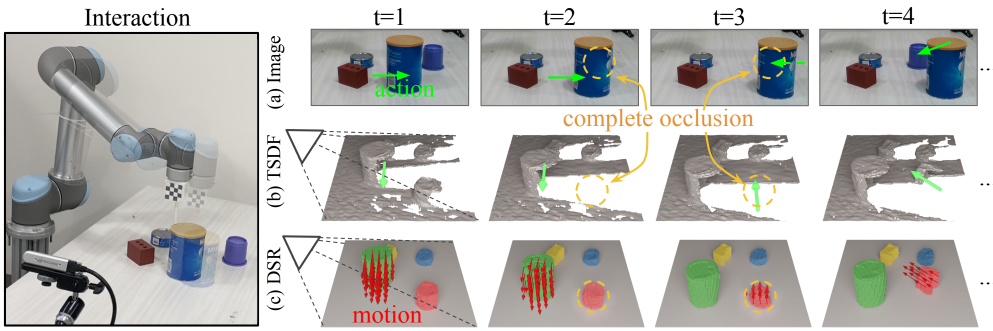

Figure 1: **Dynamic Scene Representation.** Given an applied action and a depth observation of a scene encoded as TSDF (b), the dynamic scene representation (c) is able to predict objects' motion (red arrows), infer the amodal 3D geometry of each object instance (colored voxels), and maintain the object persistence under occlusion (t=2, object in orange circle). Color images (a) are used for visualization only.

- **Interpretability:** DSR explicitly models object instances, geometry, and motion, makes it easy to be used out-of-the-box for high-level reasoning in robotic applications.

To learn this scene representation, we present DSR-Net, a 3D recurrent neural network that consists of two major components: 1) a scene encoder that encodes visual observations (i.e., depth images) into a volumetric 3D scene representation, and 2) a motion prediction network that takes in the 3D scene representation and an action to be performed by the robot and predicts volumetric scene flow. The scene flow is then used to spatially warp the current scene representation before combining it with the 3D scene representation of the next time step. The warping operation allows the network to aggregate information over time in a spatially coherent way. DSR-Net is trained end-to-end in simulation and then tested in the real world with a robotic manipulator on a tabletop setup. Our experiment result shows that our system achieves state-of-the-art performance in predicting the rigid body motion of novel objects under robot interaction in unstructured cluttered environments.

The contributions of our paper are three-fold. First, we introduce a new 3D dynamic scene representation (DSR) that captures object permanence, amodal completeness, and continuity – desirable properties as part of a perception stack for downstream robot manipulation tasks. Second, we propose DSR-Net, an end-to-end framework that learns such 3D representations via 3D convolutions. Third, we build a new benchmark dataset with over 80,000 simulated interactions and 1,500 real-world interactions for learning and evaluating dynamic 3D scene representations. Our experiments in both simulation and in the real-world show that DSR-Net achieves state-of-the-art performance in predicting 3D scene dynamics. Furthermore, it enables more accurate action planning in manipulation tasks such as planar pushing. Please find additional result and videos in supplementary material.

2 Related work

Learning scene (or state) representations from visual data for robot manipulation is a long-standing task in vision and robotics. Many different scene representations have been proposed for different environments, types of interaction, and applications. Our method learns an 3D scene representation for dynamic, multi-object environments under robot interactions. Here we summarize those that are most relevant to our approach.

Passive perception. Most traditional computer vision tasks such as object detection or segmentation can be considered as extracting a high-level scene representation from passive observation, such as a single RGB image. However, these 2D representations cannot be directly applied in robotic applications that need to be operated in 3D. Recently many works have studied the problem of inferring 3D scene representations from partial observations such as a single color image [6, 7] or a depth map [8, 9]. These representations are explicit, often in the form of 3D volumes or polygonal meshes. Latest papers in the field have also explored integrating neural nets for learning implicit 3D representations for objects and scenes [10, 11, 12, 13]. While these scene representations have been used for robotics applications such as object grasping [14, 15], they handle static environments only and cannot be directly applied in dynamic scenes.

Active perception. Systems that may update the camera viewpoint for exploration and representation building are often referred to as *active perception* systems [16, 17]. Cheng and Katerina [18] proposed an active vision system that actively selects new camera viewpoints for estimating 3D object

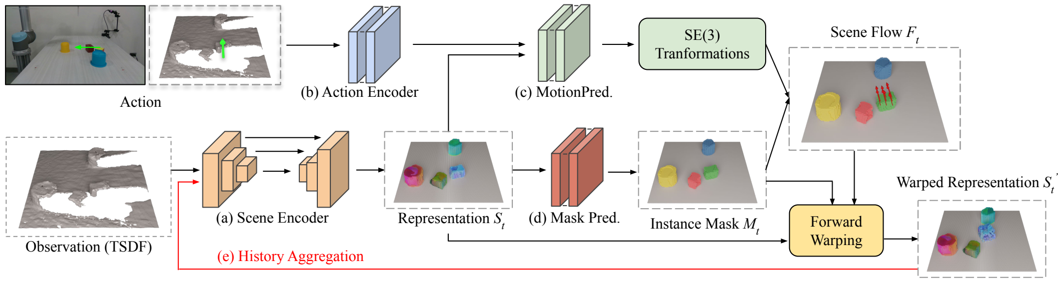

Figure 2: **DSR-Net**. DSR-Net takes in the depth observation encoded as TSDF and action as input and predicts the amodal mask of each object M_t and the voxel-wise scene flow F_t after the interaction. The scene encoder (a) outputs a representation S_t after aggregating the current observation and the history (S_t is colored by t-SNE embedding of the voxel-wise feature). S_t is then used to predict (d) amodal object instance mask M_t. In parallel, the action encoder (b) encodes the input action and the motion predictor (c) predicts object motion represented as the SE(3) transformations. The scene flow F_t is computed by combining the instance mask M_t and transformations. The warped scene representation S_t' is used as the history in the next step.

geometry and recognizing their identities. The representation learned by this system has been used for reinforcement learning [19]. There are also models that actively learn a 3D scene representation from multi-view images or videos for better 3D geometry [20, 21], shape correspondences [22, 23, 24], motion [25, 26], semantic category [27, 28], or multiple objectives [1]. While active perception systems may collect additional information about object geometry with a moving camera, they still focus on static scenes, where there is no signal about object dynamics or physics. In contrast, our model observes a robot's active interactions with objects in the scene (e.g., pushing). As a result, the scene representation can model and predict object dynamics under interaction, which is critical for task and action planning.

Interactive perception. Interactive perception is about perception facilitated by interaction with the environment [29]. An important topic in interactive perception is on learning predictive and dynamic scene representations that are conditioned on current observations and interaction for manipulation[30, 31]. Recently, a few visual predictive models have been proposed to learn an object-centric representation [32, 33, 34], as well as to model 3D motion for rigid shapes [3, 4]. However, all these works predict motion in the form of per-pixel flow, which only considers the partial, observable surface, and does not leverage past interactions and observations. Therefore, the scene representations produced by these methods are often incomplete and inaccurate. The model that is most relevant to ours is DensePhysNet [35], which learns to aggregate multiple interactions for a dense, 2D scene representation. However, it fails to model 3D relations, such as occlusion, and thus cannot provide a scene representation that maintains object permanence when there are occlusions.

3 Dynamic Scene Representation Network (DSR-Net)

In this section, we first provide an overview of DSR-Net's network design and its advantages, then we provide description on each module and how to use it in robot manipulation. Fig. 2 shows an overview of DSR-Net. At each step, the scene encoder outputs a 3D scene representation S_t that aggregates the new observation (i.e., depth) with the past scene representation S'_{t-1}. S_t is then used to predict amodal object instance mask M_t. In parallel, the motion predictor infers the object motion given the robot's action and current scene representation. The predicted motion and object instance mask are combined to compute voxel-level scene flow F_t. Finally, the scene flow F_t is used to warp the scene representation S_t to obtain S'_t that is aligned with observation in the next interaction step and used for history aggregation.

Our DSR-Net design provides four advantages compared to existing visual predictive models. First, by using a 3D volumetric representation, DSR-Net naturally models objects' amodal 3D shape, regardless of occlusion. Second, by warping the previous scene representation using the predicted motion before concatenating it with the new observation, the network manages to aggregate history information in a spatially coherent manner: the same voxel stores information of the same object from past and new observations, regardless of their motion. Third, by leveraging history information the representation is able to capture object permanence and continuity. Finally, all these properties allow the network to predict more accurate object motion and be useful for manipulation tasks.

Scene encoder (Fig. 2a): Each depth observation is encoded with a truncated signed distance function (TSDF) with voxel size 0.004m. The scene encoder concatenates the current observation (128×128×48 TSDF volume) and the warped representation from last step S'_{t-1} (the history aggregation part will includes more details). Twenty-two 3D convolution layers are applied to generate an output scene representation S_t with a size of 8×128×128×48.

Action encoder (Fig. 2b): In our setup, robots interact with the scene via pushing. The action can be discretized and represented by a tuple of integers (p_x, p_y, d), where p_x, p_y are the start coordinates of the push in Cartesian space, and d represents one of 8 pre-defined directions of a push. We represent an action as a one-hot matrix with a size of 8×128×128, where $[d, p_x, p_y]$ is 1 and other places are filled with 0. The action encoder encodes the action as two embeddings with size of 16×32×32 and 8×84×64.

Motion prediction (Fig. 2c): The motion prediction network estimates transformations for every object based on the aggregated scene representation and action applied to the scene. The motion decoder predicts k $\mathbf{SE}(3)$ transforms, one for each of the predicted masks. We fix the last transformation ($k-1$) as an identical transformation since the background is static. A $\mathbf{SE}(3)$ transform describes a rigid body transform $[R, t]$, specified by a rotation $R \in \mathbf{SO}(3)$ and a translation $t \in \mathbb{R}^3$. Under this transformation, 3D point x moves to $x' = Rx + t$. We represent rotations using a Euler transform vector. Given the predicted $\mathbf{SE}(3)$ transforms and masks, the transform layer produces a blended point cloud from the input points: $y_j = \sum_{i=0}^{k-1} M_{ij}(R_i x_j + t_i)$, where y_j is the 3D output point corresponding to voxel x_j. Then the predicted scene flow of voxel x_j is $y_j - x_j$. The motion loss $\mathcal{L}_{\text{motion}}$ is Mean Square Error (MSE) between the predicted scene flow and ground truth.

Amodal instance mask prediction (Fig. 2d): The mask predictor outputs a voxel-wise probability distribution M_t over the k classes, where k is a hyperparameter that denotes the number of objects. At each step, we compute a minimum-weighted bipartite graph matching between the mask prediction and ground-truth instances. Since the number of objects in our experiment is not very large, we enumerate the permutations p_t of $\{0, 1, \cdots, k-1\}$ to compute the optimal matching. Permutation enumeration can be replaced by the Hungarian algorithm to speed up the searching to handle a large number of objects. The matching weight $\mathcal{W}_{i,j}$ is the negative log-likelihood between a pair of masks: $\mathcal{W}_t(i,j) = M_t^{\text{gt}}(i) \cdot \log M_t^{\text{pred}}(j)$. The best order p_t is the one with the smallest minimum-weighted matching score: $\text{match}_t = \arg\min_p \sum_{i=0}^{k-1} \mathcal{W}_t(i, p(i))$. In the first step of each sequence, the p_t is computed based on match_1. For all the latter steps, p_t is computed based on the matching of the previous step match_{t-1} to encourage temporal consistency across steps. Once we find the correct permutation order for the ground truth, the loss between predicted mask and ground truth $\mathcal{L}_{mask}$ is computed with Cross Entropy loss.

Forward warping for spatially aligned history aggregation: To aggregate history, we warp the scene representation S_t with the predicted scene flow F_t and mask prediction M_t to produce features that are spatially aligned across multiple steps. Let (x_i^s, y_i^s, z_i^s) be the coordinates of voxel v_i^s in the input representation, (x_i^t, y_i^t, z_i^t) be the coordinates of a voxel v_i^t in the warped representation, and (x_i^f, y_i^f, z_i^f) is the predicted scene flow of v_i^s. The weight contribution of v_i^s to v_j^t is computed by:

$$W_{v_i^s \to v_j^t} = m_i \cdot \max(0, 1 - |x_i^s + x_i^f - x_j^t|) \cdot \max(0, 1 - |y_i^s + y_i^f - y_j^t|) \cdot \max(0, 1 - |z_i^s + z_i^f - z_j^t|),$$

where $m_i = \sum_{d=0}^{k-2} M_t[d, x_i^s, y_i^s, z_i^s]$ is the predicted probability that v_i^s belongs to any object. The last channel (d=k-1) always represents empty space. Let $S_t(i)$ represent the input feature value at v^i, then output the feature $S'_t(j)$ at v_j^t after warping is computed as: $S'_t(j) = (\sum_i S_t(i) \cdot W_{v_i^s \to v_j^t}) / \sum_i W_{v_i^s \to v_j^t}$.

Loss function. The final loss function is $\mathcal{L} = \mathcal{L}_{\text{motion}} + \alpha \mathcal{L}_{\text{mask}}$, where $\mathcal{L}_{\text{motion}}$ is the Error of motion prediction and $\mathcal{L}_{\text{mask}}$ is the loss of mask prediction and $\alpha = 5$ is a weighting factor.

3.1 Applying DSR in Robot Manipulation

We now demonstrate how DSR can be used in manipulation. Specifically, the goal of the task is to control a robot arm to push objects in the scene to match a target state. With our learned model, we perform temporally extended planning by choosing a sequence of actions that can be executed in the environment. Among different planning approaches, we choose model-predictive control (MPC) to take advantage of our predictive model.

We apply a simple shooting-based MPC method to generate and plan for a sequence of actions that minimize the cost. First, we sample sequences of actions by sampling actions around predicted masks from our DSR model, since only these actions are close to the objects. This allows us to have a much smaller sample size of actions and make our decision making faster. Then, we compute the cost based on the next state predictions, which include the pivot points and masks in the next state. Specifically, we have $\mathrm{cost}(a_1, a_2, ..., a_n) = \sum_i (\lambda_i \times L_i^{\mathrm{pos}} - \mathrm{IoU}_i)$, where $a_1, a_2, ..., a_n$ are candidate actions, L^{pos} is the Mean Square Error between target and predicted positions (computed by predicted mask) of each object, IoU_i is the IoU between the predicted mask and target state, λ_i is a weighting factor for each channel. Finally, we choose the sequence of actions that has the lowest cost.

Since DSR maintains object permanence in the representation, it enables the planning algorithm to use the full state information including the occluded objects. For example, in Fig. 3, the robot has to push an occluded cube to a target location. This is impossible with SE3-Pose-Net – since it models only visible surfaces, the object is completely missing due to occlusion (t=3) and therefore a wrong action is selected. With DSR, the control policy is able to sample actions around the occluded object to predict the next state and cost accurately. Quantitative result are shown in Sec. 5.3.

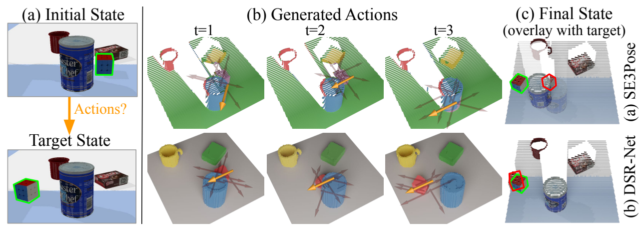

Figure 3: **Application of DSR in Planner Pushing.** (a) The goal is to generate a sequence of actions to push objects to match a target state. (b) In each step, a set of action candidates are sampled and the action with the lowest cost (yellow) is chosen to execute. At $t = 3$, SE3Pose-Net loses track of the occluded object hence choose the wrong action, while DSR-Net correctly models the occluded object and chooses appropriate actions. (c) The final state (red) of DSR-Net is much closer to the target state (green).

4 Dynamic Scene Representation (DSR) Benchmark

To quantitatively evaluate predictive models, we need a dataset that contains robot interactions and ground object motion. Since there is no existing dataset containing this information (especially with real-world robot interactions), we construct a new dynamic scene representation (DSR) benchmark that contains both simulation and real-world data for training and evaluation.

Simulation data. We use two types of objects in simulation training data: (1) cubes with different sizes $s \in [0.02, 0.04]$m, and (2) 44 shapenet objects of 5 categories: mug (5), bottle (14), can (6), phone (10), and sofa (9). For each sequence, we choose 4 objects and randomly drop them on the workspace (0.512m $\times$ 0.512m). Then the robot executes 10 random pushing actions with a simple heuristic-base policy that encourages the change of spatial order and prevents moving objects out of the workspace. Details of the policy are described in the supplementary material. In total, there are 8,000 sequences with 80,000 interactions for training. We also generate a testing dataset using YCB objects [33] with the same interaction policy. This includes 400 sequences with 4,000 interactions.

Real-world data. Our real-world setup consists of a UR5 robot with a cylinder pusher tool and two calibrated RGB-D cameras. Fig. 4 shows the setup and YCB objects [33] used in the real-world experiments. To accurately annotate the ground truth object pose under occlusion, we use an additional calibrated RGB-D camera in the setup to provide a backview of the workspace (Fig. 4 left and middle). We use the same discrete action space to collect real data. During annotation, we combine the 3D point clouds from both views to obtain a complete observation for the entire workspace. Fig. 4 right shows our annotation user interface. Users can control the object meshes' 6DoF poses with keyboard to match the pose in the scene. In total, we collect 90 sequences with 900 interaction steps.

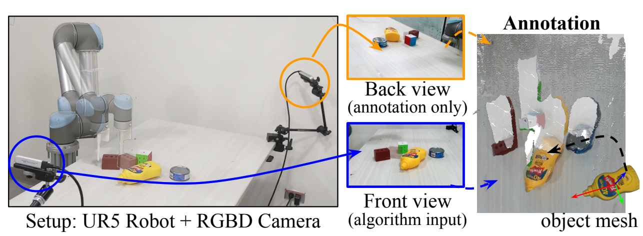

Figure 4: **Realworld Setup and Annotation UI. [left]** UR5 is used for robot manipulation. **[middle]** We capture RGB-D images using two calibrated Intel RealSense D415. The front view image is taken as input by the algorithm and the back view image is only used for annotation. **[right]** The object mesh is moved with keyboard to match the fusion of point clouds from two cameras.

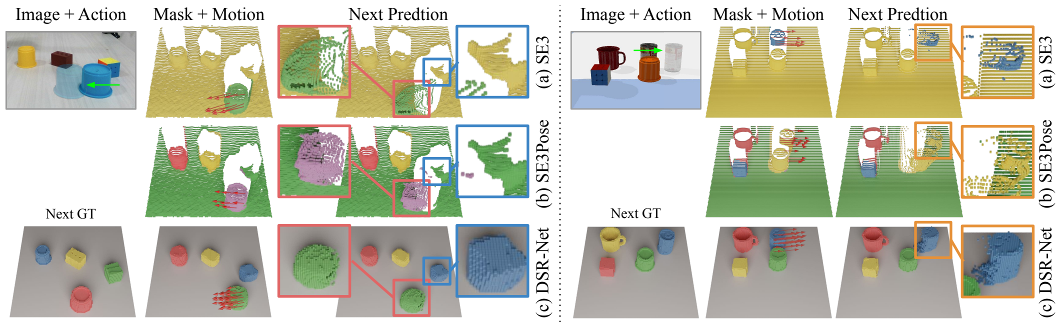

Figure 5: **Amodal Mask and Motion Prediction.** The mask and motion prediction of SE3-Net and DSR-Net in both real-world (left) and simulation (right). SE3-Net predicts only masks for moving objects and the estimated motion is limited to the visible surface. Although the mask prediction in SE3Pose-Net is not limited to moving objects, it fails to separate closed objects and miss small objects. DSR-Net produces the full 3D volume as well as masks for all objects in the scene.

Train/Test split. In simulation, all models are trained with 8,000 sequences with ShapeNet objects and tested on 400 sequences with novel YCB objects. The real-world dataset is split into 50 finetuning sequences and 100 testing sequences. In the following experiments, models labeled with "ft" are finetuned with the 50 sequences, all the other models are directly tested with realworld data without finetune. All qualitative result (except SE3 and SE3PoseNet) are using model without finetune.

5 Evaluation

We designed a series of experiments in both simulation and the real world using the benchmark data described in Sec. 4 to validate design decisions, and to compare with other models that predict future scene representations. Specifically, we want to see whether DSR-Net is able to

(1) Accurately predict object motion under different robot interactions;
(2) Aggregate the history and encodes object *permanence* and *continuity*; and
(3) Improve the performance of down-stream manipulation tasks.

5.1 Motion Prediction

First we want to evaluate the learned scene representation on predicting object motion under robots' interaction. We use the Mean Squared Error (MSE) to evaluate the predicted 3D scene flow. For image based approaches, the MSE is computed and averaged for pixels of the visible surface, same as in SE3-Net [3]. For voxel-based approaches, the MSE is computed and averaged over the voxels on visible surfaces of the object (visible) and all voxels (full) separately.

		Simulation		Real	
		visible	full	visible	full
2D	2DFlow ft [3]	8.24	-	7.63	-
	SE3-Net ft [3]	7.84	-	6.91	-
	SE3Pose-Net ft [4]	13.01	-	10.49	-
3D	3DFlow	7.34	0.093	6.80	0.094
	SingleStep	5.94	0.086	6.64	0.093
	DSR-Net	**5.54**	**0.082**	6.51	0.090
	DSR-Net ft	-	-	**3.33**	**0.048**

Table 1: **Average flow Error (MSE in cm)**

Baselines: In this experiment, we compare our algorithm with the following predictive models:

- 2DFlow [3]: it predicts per-pixel scene flow for the visible surface.
- SE3-Net [3]: it predicts per-object masks and SE3 motions
- SE3Pose-Net [4]: it predicts per-object poses, masks, and SE3 motions
- 3DFlow: it predicts per-voxel scene flow for the entire 3D volume.
- SingleStep: DSR-Net without history aggregation.

Compared with state-of-the-art predictive models. Tab. 1 shows quantitative comparisons of predicted motion. Since most voxels are static, the error of full volume is much smaller than the visible surface error. Fig. 5 shows qualitative comparisons among our model, SE3-Net, and SE3Pose-Net. The visualization suggests that the motion estimation in SE3-Net is limited to visible surface and cannot model occluded regions. In addition, the mask prediction in SE3-Net only handles the moving object, treating all other objects as background. This is because SE3-Net predicts masks based on both observation and action, where the network learns to first identify the moving objects and then

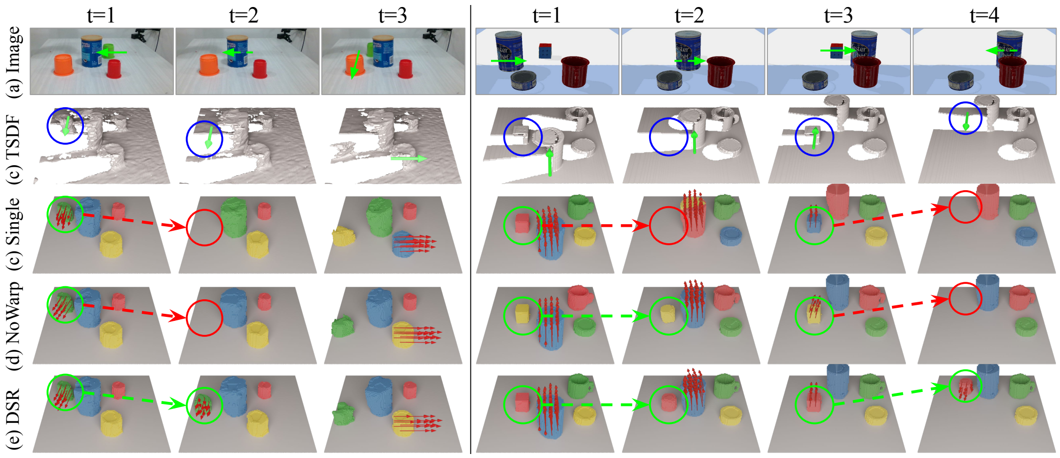

Figure 6: **Scene Representation with Object Permanence.** The TSDF and result are rendered in side view to better show occlusion cases. Object permanence is labeled in green circle and failure cases are labeled in red. At t=2, in the real-world example (left), the green cup is occluded by the can. Only DSR-Net is able to predict the permanence of the green cup. In the simulation example (right), occlusion appears in the t=2 and t=4. The difference is that at t=1-2, the Rubik's Cube is static when being occluded, and at t=3-4, the Rubik's Cube is moved and then occluded (dynamic occlusion). SingleStep fails in both cases. NoWarp can handle the first case since the history contains the information of the static Rubik's Cube, but cannot handle dynamic occlusion due to the lack of motion in the history. DSR-Net can handle both cases.

predict mask and motion for these objects only. The mask prediction of SE3Pose-Net is independent from action; therefore, it has to predict masks for all objects in the scene. However, the motion prediction of SE3Pose-Net is based on object poses without considering their detailed geometry. This fact makes SE3Pose-Net perform worse in motion prediction. In contrast, our model produces 3D amodal masks for all objects in the scene and predicts the object motion more accurately.

5.2 Temporal Information Aggregation

	Simulation		Real	
	unordered	ordered	unordered	ordered
GTWarp	0.807	0.807	0.646	0.645
SingleStep	0.753	0.526	0.613	0.485
NoWarp	0.762	0.756	0.625	0.624
DSR-Net	**0.772**	**0.767**	**0.628**	**0.628**

Table 2: **Amodal Object Mask Prediction IoU**

In this section, we evaluate whether DSR-Net is able to effectively aggregate the history information to capture object permanence and continuity. We use two types of intersection over union (IoU) scores on 3D amodal instance masks as the evaluation metric: unordered and ordered IoU. To compute unordered IoU, we obtain the object order for each step by permuting the objects' order and use the one that maximizes the average IoU over all objects as the ground truth order. The order of step t is calculated by $\text{order}_t = \arg\max_p \frac{1}{k}\sum_{i=0}^{k-1} IoU_t[M_t^{\text{gt}}(i), M_t^{\text{pred}}(p(i))]$, where k is the number of objects. For ordered IoU, we permute the object instance index once and use the order that best matches the entire sequence as the ground truth order: $\text{order}_t = \arg\max_p \sum_{s=0}^{N-1} \frac{1}{k}\sum_{i=0}^{k-1} IoU_s[M_t^{\text{gt}}(i), M_s^{\text{pred}}(p(i))]$, where N is the number of interactions. To achieve a high ordered IoU, the system needs to maintain a consistent order of object instance throughout the interaction steps. Therefore, this metric reflects the continuity of the scene representation over time. Besides, since the 3D IoU is evaluated on all the voxels in the scene regardless of occlusion, this metric also naturally measures the permanence of the scene representation under occlusion.

Baselines. In this experiment,we compare our aggregation model with following alternatives:

- SingleStep: it does not use any history aggregation.
- NoWarp: it does not warp the representation before aggregation.
- GTWarp: it warps the representation with ground truth motion (i.e., performance oracle).

Does history aggregation help in on amodal shape completion? The unordered IoU in Tab. 2 measures the quality of 3D amodal shape completion without consider the objects' identity. The result demonstrates that by effectively aggregate the past observations, our method is able to infer a more accurate scene representation in terms of modeling an object's complete 3D geometry from partial observations (+1.6% improvement in unordered IoU compare to the single step model). In the following experiments, we will evaluate the object permanence and continuity using "ordered IoU".

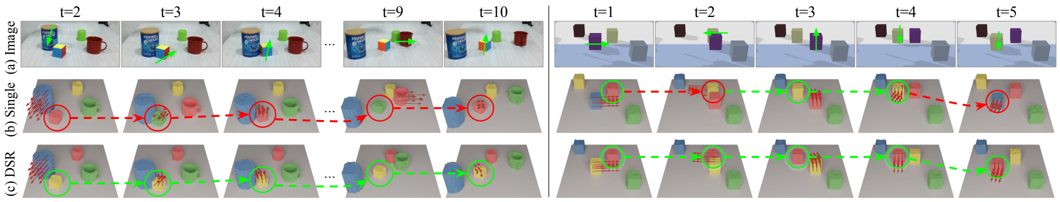

Figure 7: **Scene Representation with Object Continuity.** The mask prediction of SingleStep model (b) and DSR-Net (c) after several interactions. Color images (a) are used for visualization only. Continuous instance prediction between two consecutive steps are highlighted in green, while discontinuity is highlighted in red. In the simulation example, four identical cubes are indistinguishable in depth and the two cubes swap their positions during interaction. Our DSR-Net can track objects even when the spatial order is significant changed during interactions, while the SingleStep model fails.

Does DSR encode object permanence? To evaluate the object permanence, we examine the network's ability to infer an object's existence during occlusion. Fig. 6 shows amodal mask estimation under occlusion in both real world and simulation cases. There are two static-occlusion cases (t=1-2 in the real and simulation example), where the occluded object is not moving, and one dynamic-occlusion case (t=3-4 in the simulation), where the moving object becomes occluded. The SingleStep model fails in both scenarios. The NoWarp model can handle one of static occlusion cases, since the history contains the information of the static object. However, it cannot handle dynamic occlusion due to the lack of historical motion. In contrast, DSR-Net is able to handle both static and dynamic occlusion scenarios.

Does DSR encode object continuity? A model that captures spatiotemporal continuity should maintain a consistent object identity overtime. We evaluate this and show the results in the ordered IoU in Tab. 2. Fig. 7 presents qualitative results of mask prediction after several interactions. Unlike the SingleStep model, which is sensitive to the spatial order, our model maintains spatiotemporal continuity via consistent labeling of object instances. In the simulation demonstration, DSR-Net can even track visually indistinguishable objects, whose positions are swapped after several interactions. It proves that the continuity owes to history aggregation, instead of visual appearance. Note that this happens to align with classical findings in developmental psychology [5]. The small gap between unordered and ordered IoUs in Tab. 2 demonstrates that our DSR-Net achieves a consistent order of object instances during an interaction sequence; SingleStep has a much bigger gap, indicating that it fails to track object identity without history aggregation.

Does motion prediction help in history aggregation? To test the effect of motion prediction on history aggregation, we compare our model with NoWarp. The plot in Tab. 2 shows that, with spatial-aligned features, the algorithm produces a more accurate scene representation. In both simulation and real-world test sets, DSR-Net consistently achieves higher order and unordered IoUs. Further, if we warp the scene representation with ground truth motion as in GTWarp, the algorithm achieves even higher performance. Thus, warping features with correct object motion is helpful for aggregating history information. We conjecture that this is because the warping operation provides a spatially aligned feature representation of current and next states, making the information aggregation easier.

5.3 Apply DSR in Robot Manipulation

Finally, we evaluate the performance of using DSR in planer pushing, where the goal is to generate an action plan of a robot arm to push objects in the scene to match a target configuration. We compare the performance of our DSR model with SE3-Net [3] and SE3Pose-Net [4] using 100 target states collected from the simulation environment. We used the planning method described in Sec. 4 to generate action sequences with a length of 3 to match a pre-collected target state. Then, we compute the voxel IoU between the final full states and the groundtruth target states for evaluation. In this task, our model achieves a **0.72** IoU, outperforming SE3-Net and SE3Pose-Net, whose IoU are **0.31** and **0.32** respectively. Thus, using DSR-Net with MPC results in better state matching with target.

6 Conclusions

We have introduced a new 3D dynamic scene representation that, by design, captures object permanence, solidity, and spatio-temporal continuity. We have also proposed DSR-Net, an end-to-end framework that learns to aggregate information over multiple interactions to build such a representation from visual observations. To train and evaluate the proposed algorithm, we have presented a new benchmark with over 80,000 simulated interactions and 900 real-world interactions. Our experiments in both simulation and real world show that DSR-Net achieves state-of-the-art performance in modeling 3D scene dynamics and enables more accurate action planning in an object pushing task.

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