

Single-View 3D Reconstruction via SO(2)-Equivariant Gaussian Sculpting Networks

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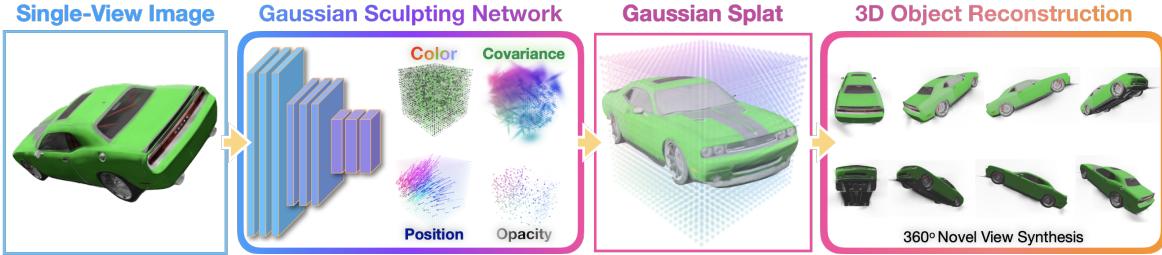


Fig. 1: Overview of the Gaussian Sculpting Network (GSN) for single-view 3D reconstruction. **Left:** Using a single observed image, the GSN transforms a canonical Gaussian splat with predicted colors, covariances, positions, and opacities. **Right:** Output from the GSN is combined to form a Gaussian splat representing the reconstructed 3D surface geometry and texture of the observed object.

Abstract—This paper introduces **SO(2)-Equivariant Gaussian Sculpting Networks (GSNs)** as an approach for **SO(2)-Equivariant 3D object reconstruction** from single-view image observations. GSNs take a single observation as input to generate a Gaussian splat representation describing the observed object’s geometry and texture (Fig. 1). By using a shared feature extractor before decoding Gaussian colors, covariances, positions, and opacities, GSNs achieve extremely high throughput ($>150\text{FPS}$). Experiments demonstrate that GSNs can be trained efficiently using a multi-view rendering loss and are competitive, in quality, with expensive diffusion-based reconstruction algorithms. The GSN model is validated on multiple benchmark experiments. Moreover, we demonstrate the potential for GSNs to be used within a robotic manipulation pipeline for object-centric grasping.

I. INTRODUCTION

Autonomous robots tasked with operating in complex, unstructured environments must be able to perceive their environment and the objects within it. In particular, perceiving the geometry and visual properties of objects is needed in order for robots to effectively plan and act using those objects. At a given instant, a robot can typically only observe part of an object’s surface and must rely on 3D reconstruction algorithms to perceive the remaining occluded geometric structures. Moreover, an equivariant reconstructed representation enables to inform consistent understanding and perform reliable interaction on the objects, eg. a reliable grasp pose on the reconstructed object should not be effected by the view angle.

Novel view synthesis offers a promising direction for robots to reconstruct detailed object models using only sparse viewpoints from their environment. For example, Neural Radiance

Fields (NeRFs), is a technique that enables novel view synthesis and 3D reconstruction by using neural implicit representations to render new views of a scene based only on a small set of observed images [1, 2]. While NeRFs have demonstrated impressive results and garnered significant interest in robotic applications, their implicit nature often hinders the explicit representation of objects’ geometric structures in 3D space, posing challenges for direct integration with robotic planning and control modules [3, 4, 5, 6, 7].

Against this backdrop, Gaussian Splatting has emerged as an explicit alternative for representing scenes and objects while also enabling novel view synthesis [8]. This approach uses a collection of Gaussian-shaped primitives to approximate a continuous scene volume along with a differentiable, highly efficient rendering technique to optimize each Gaussian against the observed views. The explicit nature of Gaussian Splatting representations allows for a simpler integration of equivariant representations, such as those based on the SO(2) rotation group, which better facilitates downstream robotics tasks.

Recent work has demonstrated the potential for Gaussian Splatting within robotic manipulation [9, 10] and navigation [11, 12]. While Gaussian Splatting has enabled novel view synthesis with an explicit representation useful for robotics, for 3D reconstruction it requires multiple diverse image observations, which are not always available. In this project, we set out to enable high throughput 3D reconstruction using single-view images with Gaussian Splatting, aiming to enable robots to understand the geometry and texture of unseen parts of objects consistently across different view angle.

The present paper makes the following contributions:

- 1) Propose and develop SO(2)-Equivariant Gaussian Sculpting Networks (GSNs), to generate Gaussian splats from single-view image observations in real time.

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- 2) Perform quantitative and qualitative evaluations of GSNs to understand relative tradeoffs in comparison to existing 3D reconstruction approaches.
- 3) We demonstrate the potential for GSN to be used within a robotic manipulation pipeline for grasping.

II. RELATED WORK

A. Multi-View 3D Reconstruction

Multi-view 3D reconstruction is a foundational topic within computer vision and robotic perception that seeks to infer the three-dimensional structure of a scene using numerous images taken from different vantage points throughout the scene. Classical approaches, such as Structure from Motion (SfM) and Multi-View Stereo enable the derivation of 3D points or volumetric representations by triangulating matched features across multiple images [13, 14]. End-to-end deep learning-based approaches have been considered including MVSNet [15] and DeepMVS [16] for depth map estimation as well as DeepSDF [17] as a continuous shape representation. More recently, neural radiance fields (NeRFs) are proposed as an approach to implicitly reconstruct volumetric scenes from sparse image observations [1, 2, 18]. Following the surge of interest in NeRFs, Gaussian splatting is developed as an explicit approach to novel view synthesis from multi-view images [8]. Notably, Gaussian splatting represents a scene as a mixture of Gaussians distributed throughout the scene and optimized using gradient descent. In contrast to these approaches, the present paper sets out to reconstruct 3D scenes using only a single observed image.

B. Single-View 3D Reconstruction

In single-view 3d reconstruction, algorithms have access to only a single image of the object whose shape they set out to estimate. Early approaches used shading cues to estimate geometric surface contours [19, 20]. Following the rise of deep learning, convolutional neural networks have been proposed for voxel-grid reconstruction from single images [21]. Image-conditioned reconstruction into point cloud representations has been proposed using convolution [22] and diffusion-based architectures [23, 24]. Following the introduction of Gaussian splatting, 3D reconstruction using splats as a 3D representation has gained interest [25, 26, 27]. Watson et al. introduce 3DiM to generate novel views with a single image using image-based diffusion, then generate 3D splats using those generated images [26]. Similarly, Feng et al. employ image-level diffusion with additional geometric constraints to improve the reconstruction speed and quality. Szymanowicz et al. propose a convolutional architecture to directly regress an output Gaussian Splat representation offering substantial speedups [25]. We set out to further improve the efficiency of single-view reconstruction based on Gaussian splatting.

III. METHOD

A. Gaussian Primitive: 3D Gaussian Splatting

A Gaussian Primitive \mathcal{G} is parameterized by 4 variables: mean $\mu \in \mathbb{R}^3$, covariance $\Sigma \in \mathbb{R}^{3 \times 3}$, RGB color $c \in \mathbb{R}^3$,

and opacity $\alpha \in \mathbb{R}$. To simplify optimization, we follow [8] and decompose Σ into scale $s \in \mathbb{R}^3$ and rotation $r \in \mathbb{R}^4$ represented using rotation quaternions. The resulting Gaussian will have the form of $\mathcal{G} = (\mu, s, r, c, \alpha)$. A scene or object can thus be represented by a collection of Gaussians that form a Gaussian Splat

$$\mathcal{S} := \{\mathcal{G}_i, i = 1, \dots, N\} = \{(\mu_i, s_i, r_i, c_i, \alpha_i), i = 1, \dots, N\}$$

The 3D Gaussian Splatting [8] renderer \mathcal{R} takes a 3D Gaussian Splat \mathcal{S} and maps it into a 2D image \mathcal{I} using camera pose $p \in \mathbb{R}^3$ and rotation $\mathbf{R} \in \mathbb{R}^{3 \times 3}$. Here, we want to find the function \mathcal{F} that inverts the process \mathcal{R} such that $\mathcal{F}(\mathcal{I}) = \mathcal{R}^{-1}(\mathcal{I}) = \mathcal{S}$. The reconstruction from this single image should preserve the correct 3D representation of the object, allowing it to render novel views of the object from viewpoints different to the input image.

Instead of letting the neural network directly predict the 5 parameters for each Gaussian, our method predicts a deviation of the parameters from a canonical cube. The canonical cube refers to a collection of Gaussians, $\bar{\mathcal{G}}_i$, that are evenly spaced apart on a unit cube with fixed initial covariances $\bar{\Sigma}$. Experimentally, this value of covariance is initialized as an identity matrix multiplied by a small constant, ie. $\bar{\Sigma} = 0.0075 \times I$. And, color and opacity values that are randomly sampled without any constraints. The resultant initial Gaussian Splat would thus have predefined $(\bar{\mu}_i, \bar{s}_i) \forall i = 1, \dots, N$ and would resemble a point cloud since the covariance scale is isotropic in \mathbb{R}^3 . To generate the predicted Gaussian Splat \mathcal{S}_{pred} , our network \mathbf{f} predicts an deviation term $\Delta\mu_i, \Delta s_i$ and values r_i, c_i, α_i for a fixed number of Gaussians N such that

$$\mathbf{f}(\mathcal{I}) = \{(\Delta\mu_i, \Delta s_i, r_i, c_i, \alpha_i), i = 1, \dots, N\}$$

The final predicted Gaussian Splat has the form

$$\mathcal{S}_{pred} = \{(\bar{\mu}_i + \Delta\mu_i, \bar{s}_i + \Delta s_i, r_i, c_i, \alpha_i), i = 1, \dots, N\}$$

B. Network Architecture

As illustrated in Fig. 2, the network feature extractor takes the image as input and encodes it into a latent vector followed by a decoding step into Gaussian parameters.

1) *Encoder*: We adopted ResNet [28] as the backbone of the encoder with some modifications. Instead of directly using the 2048 size latent vector output from the ResNet, we take the output from the second last layer that has a size of $2048 \times 7 \times 7$ latent tensor. This tensor is then fed into two 2D convolutions followed by ReLU activation and finally gets a vector of size 1×2352 after flattening the tensor. The design was chosen since, experimentally, taking the output from the ResNet with a smaller receptive field allows the network to capture more fine-grained details to reconstruct the Gaussian Splat.

2) *Decoder*: Parallel MLPs are used to decode the latent vector into Gaussian parameters $\Delta S = \{(\Delta\mu_i, \Delta s_i, r_i, c_i, \alpha_i), i = 1, \dots, N\}$. For each of the 5 parameters, we have an independent MLP layer to output $N \times \text{size of parameter}$ number of values, where N is predefined as the number of Gaussian. For example,

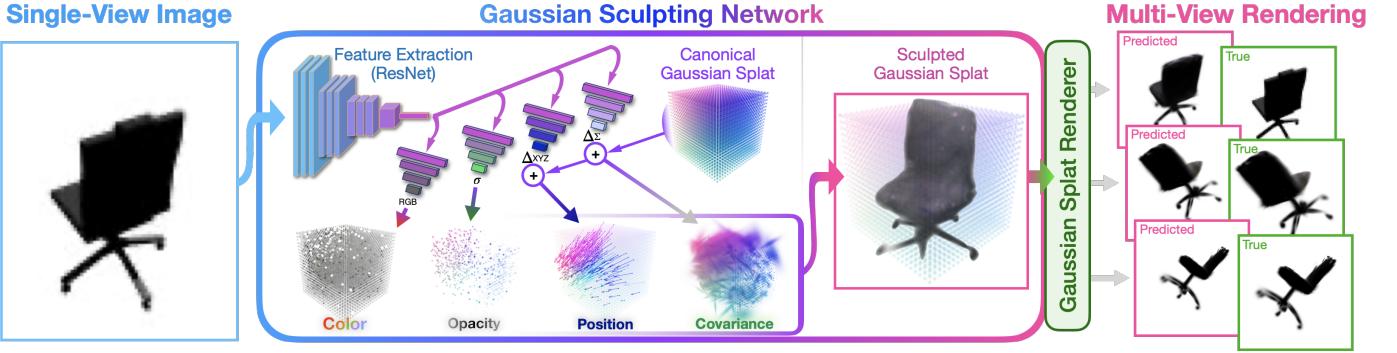


Fig. 2: SO(2)-Equivariant Gaussian Sculpting Network Architecture. Our Encoder-Decoder style network takes an input image and encodes it into a latent vector. Subsequently, a decoder with parallel MLPs decodes the latent vector into Gaussian parameters, sculpting a canonical Gaussian Splat into a 3D object presented in the input image. Finally, we perform multi-view rendering to obtain various novel views for loss calculation.

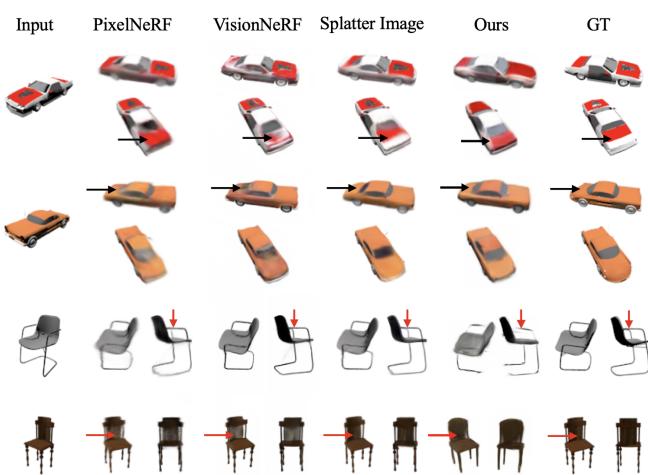


Fig. 3: Qualitative single-view reconstruction comparison. We reused the visualization results from Splatter-Image and added our results for comparison.

Method	Chairs			Cars		
	PSNR \uparrow	SSIM \uparrow	Lpips \downarrow	PSNR \uparrow	SSIM \uparrow	Lpips \downarrow
SRN	22.89	0.89	0.104	22.25	0.88	0.129
CodeNeRF	23.66	0.90	0.166	23.80	0.91	0.128
PixelNeRF	23.72	0.90	0.128	23.17	0.89	0.146
Splatter	24.43	0.93	0.067	24.00	0.92	0.078
GSN (ours)	24.35	0.90	0.117	24.12	0.92	0.100

TABLE I: ShapeNet-SRN: Single-view 3D reconstruction. Our model is trained on a machine with RTX A6000. The statistics for other methods are adopted from experiments in prior works. The result shows that our model performs better than some of the prior methods, while remain comparable for similar works that reconstruct a Gaussian Splat.

to describe $\Delta\mu$ for one Gaussian, we need three values, $\Delta\mu_x, \Delta\mu_y, \Delta\mu_z$, so the output of the MLP for $\Delta\mu$ will have $N \times 3$ output size. For each MLP, there consists of two fully connected linear layers and the first linear layer is followed by a ReLU activation. For predicted scale $\bar{s}_i + \Delta s_i$, we apply ReLU activation followed by addition with a small scalar constant $\epsilon \in \mathbb{R} : \epsilon > 0$ to ensure that the covariance is positive definite. For predicted rotation r_i , we normalize r_i without making the real quaternion term positive, whereas for color c_i and opacity α_i , we apply a channel-wise sigmoid function.

Method	FPS \uparrow
Splatter	50
GSN (ours)	164

TABLE II: Performance during inference. Our method is significantly faster than the recent baseline for generating Gaussian Splat from a single input image.

C. Loss Formulation

To train the neural network \mathcal{F} , we aim to minimize the difference between a set of ground truth images with different camera poses and the rendered images from a predicted Gaussian Splat. Specifically, given an input image of an object, the network predicts a 3D Gaussian Splat conditioned on this input image. We then render the Splat from different views and compare it with available ground truth images taken from those viewpoints.

$$\begin{aligned}\tilde{\mathcal{I}}_i &:= \mathcal{R}(\tilde{\mathcal{S}}, p_i, \mathbf{R}_i) \\ \mathcal{I}_i &= \mathcal{R}(\mathcal{F}(\mathcal{I}_{input}), p_i, \mathbf{R}_i) \\ \mathcal{L}_{image} &= \frac{1}{k} \sum_{i=1}^k f_{image}(\tilde{\mathcal{I}}_i, \mathcal{I}_i)\end{aligned}$$

where $\tilde{\mathcal{I}}_i$ denotes the ground truth image i , $\tilde{\mathcal{S}}$ denotes some hypothetical ground truth Gaussian Splat that would generate $\tilde{\mathcal{I}}$ and k represents the number of sampled ground truth images with different camera poses for each object.

We adopt 3 different losses: L2, Lpips, and DSSIM as inspired by [25], [8], and [29] which shows that L2 and DSSIM contribute to shaping the overall structure and color and Lpips help learn more fine-grained details.

To achieve SO(2) invariance regarding the view angle, the input image is rotated along the camera's principal axis by a random angle T and then processed by the same network to produce a rotated splat. We minimize an extended Chamfer Distance between the rotated splat and the unrotated splat after applying the same rotation around the camera's principal axis.

$$\mathcal{L}_{rot} = \mathcal{L}_{Chamfer}(\mathbf{T}(\mathcal{F}(\mathcal{I}_{input})), \mathcal{F}(\mathbf{T}(\mathcal{I}_{input})))$$

The Extended Chamfer Distance, similar to the well-known Chamfer Distance for point cloud, applies additional element-wise L2 loss on color, scale, rotation, and opacity for the nearest neighbors

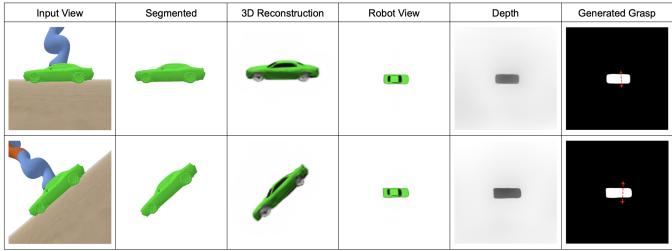


Fig. 4: Generated grasp using Dex-Net 2.0 from novel views rendered from 3D Gaussian Splat generated by our model with canonical view and rotated view as input. Dex-Net can generate grasps for cars with grasp quality q-vvalue=0.733 with canonical view and q-value=0.614 for rotated view.

IV. EXPERIMENT

To evaluate our proposed framework, we trained our model against the chairs and cars dataset provided by [25], and demonstrate possible usage for robot grasping task.

A. Single-View 3D reconstruction on Chairs and Cars

In this task, the model predicts a 3D representation (Gaussian Splat in this case) of an object given a single input view of that object. Novel target views are then rendered from this representation and the performance is measured by comparing these rendered images with the ground truth images. We follow the practice of prior works, such as [30] [1] [31] [32], and measure the performance in terms of the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity (SSIM) and perceptual quality (LPIPS). For PSNR and SSIM, higher values indicate better quality, whereas for LPIPS, lower values are preferable. For datasets, we adopt the ShapeNet-SRN dataset for cars and chairs from [31] which aligns with the recent single-view Gaussian Splat generation model [25].

Results. We trained our model on the chair and car datasets for four days, using a batch size of 8, until convergence. Compared to the Splatter Image model [25] that requires seven days to converge, our model converges faster and is less expensive to train. Table I and II and Figure 3 show how our model performs quantitatively and qualitatively to other baselines. As demonstrated, our method performs roughly 3 times faster than the next fastest method (splatter-image) during inference while having comparable quantitative image reconstruction quality to other recent baselines. Qualitatively, we observe that while our model accurately captures the overall geometry, it still struggles with extremely fine-grained details, especially in the chair dataset, which includes many thin leg and handle structures. This also explains the larger disparity in LPIPS scores for the chair dataset, as LPIPS focuses more on details, whereas PSNR and SSIM consider more of the geometric similarity.

B. SO(2)-Equivariant Grasp Simulation

We also evaluate the effectiveness of our model for practical robot manipulation tasks to gauge its suitability for real-world applications. In our experiment, a Kuka arm is used along with an external camera placed on the opposite side of the robot in the Bullet simulation [33]. In addition, the input

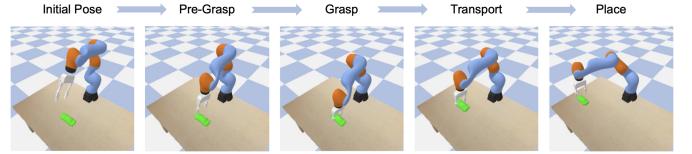


Fig. 5: Simulation of Robot Grasping using Kuka manipulator in Pybullet. Check out the video demo here: <https://youtu.be/USOLfgzOTf4>

view is randomly rotated along the camera’s principal axis, representing imperfect view angle to test the the ability of the model to represent the SO(2) invariance with same input image feature. This setup reflects practical robot manipulation scenarios where the camera cannot observe the geometry of the object that the robot can act on. Without ground truth observation from the robot’s viewpoint, GSN becomes useful in predicting the geometry and texture of the object’s occluded parts, enabling the robot to generate a reliable grasp.

Specifically, as shown in Figure 4, the model receives one input image and reconstructs the full object in Gaussian Splat representation. This Gaussian Splat is then rendered into a view from the robot’s perspective, such as a bird’s-eye view. Based on this robot view, we perform depth estimation using MiDaS [34] to generate a depth map and Segment Anything (SAM) [35] to produce a binary mask. Finally, the rendered robot view, depth map, and binary mask are utilized for robot grasp prediction by Dex-Net 2.0 [36]. To generate a robot motion plan to achieve the grasp pose, we use the inverse kinematics solver in PyBullet to control the Kuka arm. The simulation result is shown in Figure 5, capturing snapshots at five different stages during grasping.

We observed that our model is able to represent the same object almost concisely across different view angle. In Figure 4, the rotated view produce the same Splat representation and results in consistent depth estimation and grasp generation. In addition, we found that our model capture the general geometry and texture even when the input view of the object lacks rich information. Specifically, due to the compatibility issues with the object mesh, the Shape-Net car does not display the color of the windows and wheels. However, our model accurately recovers the correct color of these parts.

V. CONCLUSION

This paper makes three central contributions: (1) a SO(2)-Equivariant Gaussian Sculpting Network for real-time single-image 3D reconstruction, (2) experiments validating the sculpting network design, and (3) demonstrations to highlight how GSN is applicable to a robotic grasping pipeline and remain consistent under different SO(2) transformation along the camera’s principal axis. Experiments demonstrated the high-throughput of GSNs and suggest their potential for application to robotic perception tasks, especially in a cluttered scene where multiple objects reconstructions are required. Results from this study suggest future directions to (1) further improve reconstruction quality by focusing on fine-grained texture detail, (2) craft a better loss between splat to learning the equivariant representation, and (3) extend to a more general group, such as SO(3) or SE(3).

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