Spurfies: Sparse-View Surface Reconstruction Using Local Geometry Priors

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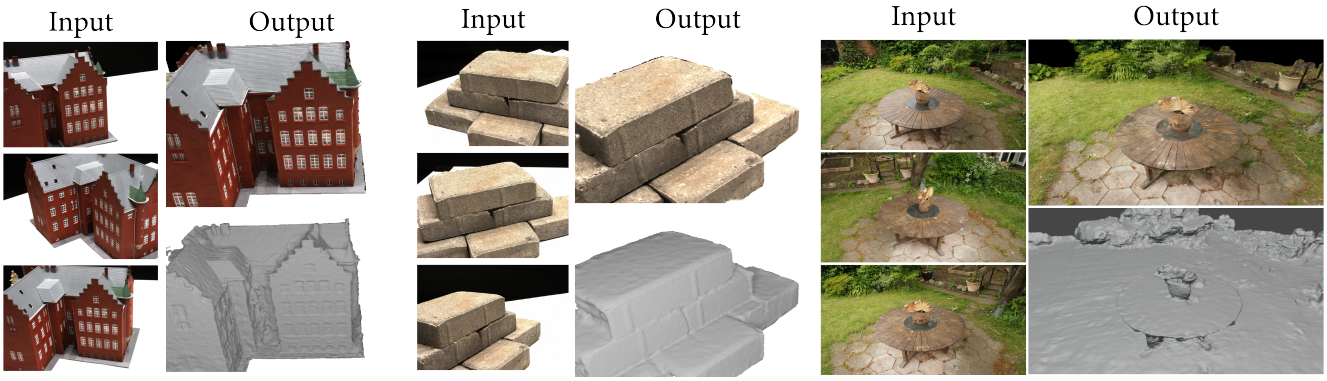

Figure 1. Spurfies leverages synthetic data to learn local surface priors for surface reconstruction from few images. Our model significantly outperforms previous methods and can be applied to both bounded (DTU dataset, left) and unbounded scenes (Mip-NeRF360, right).

Abstract

We introduce Spurfies[1], a novel method for sparse-view surface reconstruction that disentangles appearance and geometry information to utilize local geometry priors trained on synthetic data. Recent research heavily focuses on 3D reconstruction using dense multi-view setups, typically requiring hundreds of images. However, these methods often struggle with few-view scenarios. Existing sparse-view reconstruction techniques often rely on multi-view stereo networks that need to learn joint priors for geometry and appearance from a large amount of data. In contrast, we introduce a neural point representation that disentangles geometry and appearance to train a local geometry prior using a subset of the synthetic ShapeNet dataset only. During inference, we utilize this surface prior as additional constraint for surface and appearance reconstruction from sparse input views via differentiable volume rendering, restricting the space of possible solutions. We validate the effectiveness of our method on the DTU dataset and demonstrate that it outperforms previous state of the art by 35% *in surface quality while achieving competitive novel view synthesis quality. Moreover, in contrast to previous works, our method can be applied to larger, unbounded scenes, such as Mip-NeRF360.*

1. Introduction

3D surface reconstruction just from a small number of 2D input images has been an important goal in computer vision in the recent years. While we entered an era in which we can get high-quality reconstructions from a large number of carefully captured images through recent advances in SDF-based neural fields [33, 36] or surfels in the form of 2D Gaussians [14], we still lack the capabilities to perform this task from a sparse set of views. The key challenge in this setup is the under-constrained nature of the optimization problem at hand: there are simply too many potential combinations of geometry and appearance that would satisfy the sparse set of given image observations.

The usual way to solve such under-constrained tasks is to introduce regularization or priors into the formulation. Typical approaches include feature consistency [15] and cues from monocular depth [48], multi-view stereo [32, 40], or structure from motion [10].

More recently, learned priors have been introduced, e.g. from pre-trained 2D diffusion models [41]. They have been shown to clearly improve reconstruction quality from a few observations, being able to hallucinate missing appearance details. However, a clear limitation of diffusion-based ap-

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proaches is that they require large amounts of training data in order to generalize to the diverse domain of appearances that 3D scenes can have.

In this work, we make the key observation that the space of local surface geometry is much less diverse than that of surface appearance and make the following three key assumptions: (1) we argue that much less training data is needed to learn a useful surface geometry prior than to learn a prior about appearance, (2) that synthetic data can serve well as training data for geometry as the domain gap between real and synthetic data for geometry is smaller, and (3) that a geometry prior already serves as a useful constraint to appearance reconstruction from only a few observations. To verify, we design an architecture that explicitly disentangles geometry from appearance modeling, while still jointly optimizing both during the reconstruction process. With this architecture, we are able to pre-train the geometry part of our network on synthetic data and enable it to learn the space of common surface structures. During test-time optimization, the pre-trained geometry branch then provides regularization for the joint SDF and appearance reconstruction of the scene.

As neural field representation we opt for a point-based neural field [44], with points initialized by DUSt3R [35], which we extend to model signed distance functions (SDFs) instead of density. On the neural point cloud we store separate features for SDFs and appearance in local neighborhoods. The representation is rendered via volume rendering by aggregating and processing neighboring features for sample points along the ray. Signed distance and radiance are predicted by a pre-trained geometry and a per-scene appearance decoder, respectively.

We show that Spurfies

- outperforms previous methods in sparse-view surface reconstruction quality by a large margin,
- reaches state-of-the-art novel view synthesis quality, and
- can be applied to larger, unbounded scenes,

by relying on recent advances in point reconstruction [35] and a local surface prior trained purely on synthetic data.

2. Related Work

2.1. Surface Reconstruction from Images

Dense Views Since NeRF [25] revolutionized inverse graphics by parameterizing implicit radiance fields as neural networks trained via differentiable volume rendering, there have been many approaches to directly reconstruct 3D surfaces in a similar manner. NeuS [33] and VolSDF [45] reformulate the density of radiance fields based on a signed distance function to implicitly learn a surface representation via inverse rendering. Follow-up works like MonoSDF [48], Geo-Neus [10], RegSDF [49], and NeuRIS [32] leverage depth and normal estimation, sparse geometry from structure from motion (SfM), and photometric consistency constraints in multi-view stereo for additional regularization. Another line of research [20, 36, 42, 46, 52] focuses on accelerating training and rendering of neural surface representations by incorporating explicit data structures like multi-resolution hash grids [26]. To this end, following the breakthrough of fully explicit 3D Gaussian Splatting [18], SuGaR [13], 2D GS [14], and DN-Splatter [31] try to tame Gaussians for accurate mesh reconstruction. While high-fidelity surface reconstruction is now possible with training in the matter of minutes, all these approaches assume dense captures of the scene in the form of a large number of input images.

Sparse Views To reduce the number of input views and therefore enable applications to more real-world settings, geometric priors can further constrain the space of possible reconstructions. Approaches for generalizable surface reconstruction [22, 23, 29, 40, 43] learn such priors on additional training scenes. Specifically, SparseNeuS [23] fuses 2D features into a cascade of coarse-to-fine voxel grids for end-to-end SDF prediction from sparse input views. These predictions can be used as initialization for per-scene fine-tuning. VolRecon [29] and ReTR [22] leverage transformer architectures for rendering conditioned on similar fused voxel features. C2F2NeUS [43] replaces imprecise, regular voxel grids with view-based cascade cost frustums. S-VolSDF [40] combines VolSDF [45] with CasMVSNet [12] by supervising the former with probability volumes from the latter, which in turn produces depth hypotheses used for sampling in a finer MVS stage. All of these approaches train a surface prior on image data, limiting generalization to scenes close to the training distribution.

NeuSurf [15] proposes a two-stage approach by first training an unsigned distance field given sparse point clouds from SfM [53], which is used as a coarse geometric constraint for fitting a fine signed distance field in the second stage. However, it relies on global representations resulting in limited efficiency, scalability, and level of detail. In contrast to that, our method trains a local geometric prior on general, synthetic, texture-less meshes, requiring little data for generalization. We achieve this by decomposing our architecture into geometry and appearance branches build on a point-based representation. Given the recent breakthrough of DUSt3R [35] for stereo 3D point cloud reconstruction via large-scale (pre-)training of transformer architectures, point-based representations render an elegant solution to obtain watertight surfaces.

2.2. Point-based 3D Representations

Point-based 3D representations [1, 18, 28, 44] equip point clouds obtained from RGB-D sensors, MVS, or SfM pipelines with additional learnable parameters. Point-

NeRF [44] decodes these features with small MLPs to represent a radiance field fitted on dense input views. Subsequent works employ similar representations for relighting and deformation [21], single-view reconstruction [37], and object generation [30]. 3D GS [18] and follow-ups for surface [13, 14, 31], generalizable [5, 7, 38], or non-rigid [8, 24, 39] reconstruction use optimizable Gaussian parameters and spherical harmonic coefficients for view-dependent RGB, enabling much faster rasterization-based rendering without any neural components. However, the explicit nature is hardly compatible with learning of neural priors without loosing the efficiency advantages. Therefore, our architecture is based on neural point clouds with individual geometry and appearance decoding branches for data-efficient pre-training of a local surface prior only.

3. Prerequisites

Given a sparse set of $N = 3$ RGB images $\mathcal{I} = \{\mathbf{I}_i \,|\, i \in 1, \dots, N\}$, known camera poses $\mathcal{V} = \{\mathbf{v}_i \,|\, i \in 1, \dots, N\}$ and a point-cloud $\mathcal{P} = \{\mathbf{p}_i \,|\, i \in 1, \dots, M\}$ that we obtain from DUSt3R [35], we aim to reconstruct a surface $\mathcal{S}$. The reconstruction quality depends upon the point-cloud $\mathcal{P}$. In the following, we denote all predictions from our model with the $\hat{}$-symbol. We choose a continuous implicit surface representation using a signed distance field $\hat{s}(\mathbf{x})$ and use the approach from VolSDF [45] by attaching a volumetric radiance field with density $\hat{\sigma}(\mathbf{x})$ and radiance $\hat{r}(\mathbf{x})$ to leverage its graceful optimization properties via backpropagation and gradient descent. The density is derived from the signed distance via:

$$\hat{\sigma}(\mathbf{x}) = \begin{cases} \frac{1}{2} \exp\left(\frac{\hat{s}(\mathbf{x})}{\beta}\right) \cdot \alpha & \text{if } \hat{s}(\mathbf{x}) \leq 0 \\ \left(1 - \frac{1}{2} \exp\left(-\frac{\hat{s}(\mathbf{x})}{\beta}\right)\right) \cdot \alpha & \text{if } \hat{s}(\mathbf{x}) > 0\,, \end{cases} \tag{1}$$

where α and β are learnable parameters that control the sharpness of the surface. For a given ray $\mathbf{x}(t) = \mathbf{o} + t \cdot \mathbf{d}$, we use importance sampling to sample points with intervals Δ_i to obtain density $\hat{\sigma}_i$ and radiance $\hat{r}_i$. We then compute the final pixel colors $\hat{C}_{u,v}$ for pixel (u, v) via transmittance computation and ray accumulation from NeRF [25, 45].

4. Spurfies

As the combination of signed distance fields with volumetric rendering introduced in the last paragraph has shown to provide high-quality surface reconstructions from many observations, the question is how to enable sparse-view reconstruction by representing $\hat{s}(\mathbf{x})$ and $\hat{r}(\mathbf{x})$ with a data prior that was obtained from a training dataset. We introduce our technique that we name *Spurfies* (Figure 2). It extends volumetric rendering by two key components: **(1) A neural point representation** (Section 4.1), where each point $\mathbf{p}_i$ is associated with geometry and appearance latent codes $\mathbf{f}_i = (\mathbf{f}_i^g, \mathbf{f}_i^a)$ that enable local processing and effective disentanglement of both modalities. **(2) A local geometry prior** (Section 4.2) to mitigate the shape-radiance ambiguity inherent in sparse-view reconstruction [51]. We argue that there is less variety in geometry than in appearance such that disentanglement in combination with a strong geometry prior is key. Unlike previous works that rely on multi-view stereo data during training, it is sufficient to obtain such a local prior from a synthetic object dataset (ShapeNet [4]).

4.1. Neural Point Representation

We use a distributed representation that is applicable to whole scenes by attaching disentangled latent codes $\mathbf{f}_i^g, \mathbf{f}_i^a$ to the points $\mathbf{p}_i$ to form a neural point cloud. To regress $\hat{s}(\mathbf{x})$ and $\hat{r}(\mathbf{x})$ at a query location $\mathbf{x}$, we use K neural points $\mathbf{p}_k$ within a local neighborhood of radius R.

Local Processing. We map the point features to the relative query location:

$$\mathbf{f}_{kx}^g = G_{\text{LP}}(\mathbf{f}_k^g, \mathbf{x} - \mathbf{p}_k)\,, \tag{2}$$
$$\mathbf{f}_{kx}^a = A_{\text{LP}}(\mathbf{f}_k^a, \mathbf{x} - \mathbf{p}_k)\,, \tag{3}$$

where G_{LP} and A_{LP} are two small MLPs. The resulting intermediate latent codes $\mathbf{f}_{kx}^g$ and $\mathbf{f}_{kx}^a$ encode local geometry and appearance. The use of relative positions $\mathbf{x} - \mathbf{p}_k$ makes our architecture local and translation invariant, a property that allows application on larger scenes [44].

Signed Distance Regression. We then directly map the geometry features to signed distance values and interpolate them at the query location via:

$$\hat{s}(\mathbf{x}) = \frac{\sum_{k=1}^{K} w_k \cdot \hat{s}_{kx}}{\sum_{k=1}^{K} w_k}, \quad \hat{s}_{kx} = G_{\text{REG}}(\mathbf{f}_{kx}^g), \tag{4}$$

where G_{REG} is another MLP and the weighting function $w_k = e^{-\lambda \|\mathbf{x} - \mathbf{p}_k\|_2^2}$ is modelled using radial basis functions (RBFs). We use Gaussians as the distance kernel with variance λ, which controls the influence of the neighboring neural points $\mathbf{p}_k$. In addition, the RBF weights are bounded between $[0, 1]$ providing stability during the training process.

Radiance Regression. For radiance prediction, we first interpolate the local scene appearance encoded by neighboring points and subsequently regress the radiance with a small MLP A_{REG}:

$$\hat{r}(\mathbf{x}, \mathbf{d}) = A_{\text{REG}}(\mathbf{f}_x^a, \mathbf{d}), \quad \mathbf{f}_x^a = \frac{\sum_{k=1}^{K} w_k \cdot \mathbf{f}_{kx}^a}{\sum_{k=1}^{K} w_k}\,, \tag{5}$$

with view direction $\mathbf{d}$, following previous work [44]. The interpolation weights w_k are computed using the same RBF

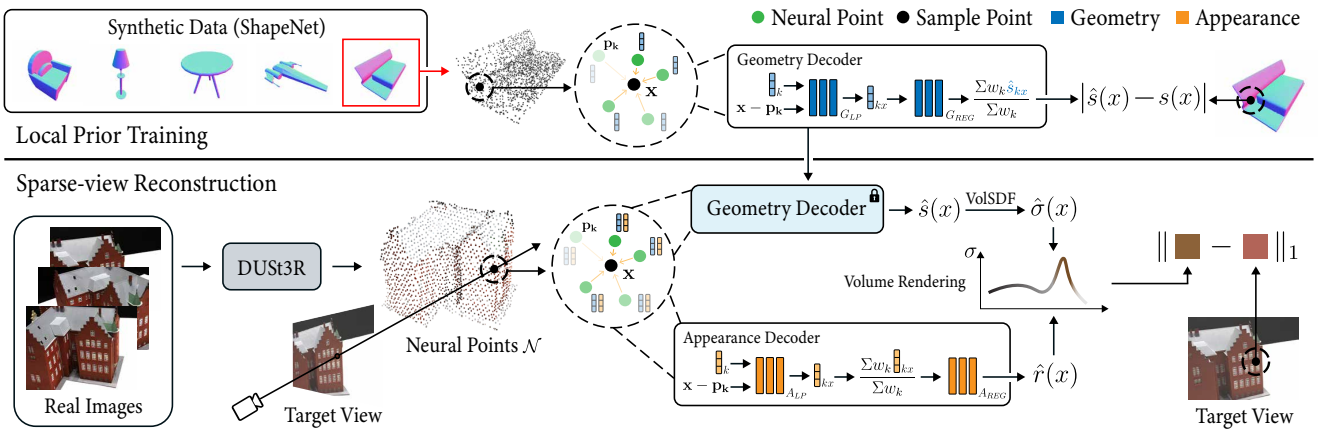

Figure 2. **Method overview:** 1) **Preprocess:** given a sparse set of input views, we make use of DUSt3R [35] to predict points $\mathcal{P}$. 2) **Representation:** The points serve as basis for a neural point representation that stores disentangled features $\mathbf{f}^a$, $\mathbf{f}^g$ for geometry and appearance on each point. 3) **Local Prior** (top): We learn a local geometry prior G_{LP} & G_{REG} over a subset of shapes from the synthetic ShapeNet dataset [4] by optimizing to predict ground truth SDF. 4) **Spurfies** (bottom): We make use of the prior for surface reconstruction from sparse images, only optimizing the latent codes $\mathbf{f}^a$, $\mathbf{f}^g$ and the color MLPs A_{LP} & A_{REG} to reconstruct images via volume rendering.

kernel as in the SDF regression, ensuring smooth blending of local appearance information. Finally, $\hat{s}(\mathbf{x})$ and $\hat{r}(\mathbf{x})$ are rendered via volumetric rendering (c.f. Section. 3).

4.2. Local Priors

To address the shape-radiance ambiguity [51] inherent in sparse-view settings, we propose a novel approach that diverges from traditional multi-view stereo (MVS) based methods. While previous sparse-view reconstruction techniques [23, 29] often rely on MVS networks with cost volumes and use 3D CNNs to regress SDF and color, we leverage the disentangled nature of our proposed neural point representation. Notably, in our approach the geometry and appearance branches are completely separate. This enables us to learn generalizable local geometry priors in the networks G_{LP} and G_{REG} on a synthetic dataset with available ground-truth geometry. During inference, we keep the geometry networks frozen and only optimize the geometry latent codes together with the full appearance branch.

4.2.1 Training

To train the geometry network effectively, we require a set of query points $\mathcal{X} = \{\mathbf{x}_i\}_{i=1}^{S}$ with corresponding ground-truth signed distances $s(\mathbf{x}_i)$.

For each training mesh, we also sample a neural point-cloud $\mathcal{N} = \{(\mathbf{p}_i, \mathbf{f}_i^g)\}_{i=1}^{\text{M}}$. It consists of global point coordinates and randomly initialized geometry latent codes for each point.

We follow the procedure outlined in [3, 27] to sample the query points and evaluate the ground-truth SDF. To enhance the network's robustness to noise, we add Gaussian noise to the neural point locations with variance 0.005. Our training dataset is a small subset of ShapeNet [4], consisting of five object classes: sofas, chairs, planes, tables, and lamps. The local prior is trained on a total of 50 objects, with 10 objects randomly selected from each class.

This training approach ensures that our geometry network learns a robust and generalizable representation of local shapes using SDF ground truth as opposed to using incomplete depth maps or unreliable inverse renderings, which require much more diverse training data and are significantly more expensive. A key contribution is to show that a small and accurate synthetic dataset is sufficient to learn a prior that generalizes to general, large scale scenes. Upon increasing the dataset size, the reconstruction quality did not improve, and the performance saturated.

4.2.2 Loss Functions

We train the local prior using the following loss functions.

SDF Loss. We take the absolute difference between the ground-truth $s(\mathbf{x}_i)$ and the predicted SDF value $\hat{s}(\mathbf{x}_i)$ [26]. We further weight the loss closer to the surface by scaling with the inverse of the ground-truth distance and add a small number to prevent division by zero:

$$\mathcal{L}_{\text{SDF}} = \sum_{i=1}^{S} \frac{|s(\mathbf{x}_i) - \hat{s}(\mathbf{x}_i)|}{|s(\mathbf{x}_i)| + \epsilon}. \tag{6}$$

Eikonal Loss. We use the Eikonal loss to regularize the Signed Distance Function (SDF) [11] and ensure the properties of a true distance field:

$$\mathcal{L}_{\text{Eik}} = \sum_{i=1}^{S} \left(\|\nabla \hat{s}(\mathbf{x}_i)\|_2 - 1\right)^2. \tag{7}$$

Total Variation Loss. We find that regularizing the geometry latent codes, such that nearby neural points are closer in latent space, is beneficial for surface reconstruction. Thus, we introduce a total variation loss:

$$\mathcal{L}_{\mathrm{TV}} = \sum_{i=1}^{M} \sum_{k \in \mathcal{K}(i)} \frac{\|\mathbf{f}_i^g - \mathbf{f}_k^g\|_1}{\|\mathbf{p}_i - \mathbf{p}_k\|_2}, \tag{8}$$

where $\mathcal{K}(i)$ is the local neighborhood of neural points around the point with index i [44]. This results in smooth changes to the regressed local surface (c.f. Section 5.2).

Training Objective. In total, we find the optimal parameters of G_{LP}, G_{REG}, and $\mathbf{f}_i^g$ by minimizing:

$$\mathcal{L}_{\mathrm{Prior}} = \mathcal{L}_{\mathrm{SDF}} + \lambda_{\mathrm{TV}} \cdot \mathcal{L}_{\mathrm{TV}} + \lambda_{\mathrm{Eik}} \cdot \mathcal{L}_{\mathrm{Eik}}, \tag{9}$$

where the factors λ weigh the individual loss terms.

4.3. Sparse-view Reconstruction

We incorporate the knowledge learned from the local prior to the volume rendering pipeline. We achieve this by keeping the geometry network fixed and only optimizing latent codes and the appearance network using the following established rendering losses for sparse-view reconstruction. For details about loss functions from previous works and the individual weights we refer to the appendix.

Rendering Loss. To ensure that our reconstructed model accurately reproduces the input images, we employ a rendering loss. It is defined as the L_1 distance between the rendered and ground-truth images:

$$\mathcal{L}_{\mathrm{Ren}} = \sum_{i,u,v \in \mathcal{I}} \|\hat{C}_{i,u,v} - C_{i,u,v}\|_1, \tag{10}$$

where $\hat{C}_{i,u,v}$ is the pixel color of pixel (u, v) of image i, and $C_{i,u,v}$ the respective ground truth value.

Feature Consistency Loss. We use a feature consistency loss $\mathcal{L}_{\mathrm{FC}}$ from NeuSurf [15]. It minimizes the differences in VisMVSNet [50] features between the projections of surface points onto different views. This encourages consistency across views and support reconstructing finer surface details.

This loss minimizes the differences in feature space between the projections of each surface point onto different views. By doing so, we encourage consistency across views and support reconstructing finer surface details.

Pseudo SDF Loss. We adapt a pseudo SDF loss $\mathcal{L}_{\mathrm{Pseu}}$ from previous work [10] for our approach. It is minimized when the neural points $\mathbf{p}_i$ lie on the zero level set of the predicted SDF $\hat{s}$, i.e., on the surface.

Optimization Objective. In total, we find the optimal parameters of A_{LP}, A_{REG}, $\mathbf{f}_i^g$, and $\mathbf{f}_i^a$ by minimizing:

$$\mathcal{L}_{\mathrm{Rec}} = \mathcal{L}_{\mathrm{Ren}} + \lambda_{\mathrm{FC}} \cdot \mathcal{L}_{\mathrm{FC}} + \lambda_{\mathrm{Pseu}} \cdot \mathcal{L}_{\mathrm{Pseu}} + \lambda_{\mathrm{TV}} \cdot \mathcal{L}_{\mathrm{TV}}, \tag{11}$$

obtaining the final scene reconstruction.

5. Experiments

In this section, we compare Spurfies against previous methods for sparse-view surface reconstruction. We begin by introducing the used datasets, baselines and metrics, before presenting reconstruction results in Section 5.1 and an ablation study with additional feature analysis in Section 5.2.

Datasets. In our evaluation process, we utilize the DTU dataset [16], a comprehensive collection of object scans featuring 49 images per scan, each with a resolution of 576×768. The dataset provides point clouds, camera intrinsics, and poses, making it ideal for assessing sparse-view reconstruction methods. We observe that various approaches in the literature differ in their selection of input views for evaluation. Adopting the strategy employed by PixelNeRF [47], we take views 22, 25, and 28 from each scan as input, leaving 25 test views. The setup represents a dispersed view distribution with low overlap. For evaluation, we follow previous work S-VolSDF [40], using the same set of scans from the DTU dataset for our approach and all baseline methods. We also evaluate on Mip-NeRF360 [2], a dataset of larger, unbounded scenes, captured from dense views. Since none of the previous works evaluates sparse-view reconstruction on Mip-NeRF360, we randomly choose a subset of three views to test. Note that none of our test scenes are in the training data of DUSt3R [35].

Baselines. We compare our work against multiple state-of-the-art sparse-view reconstruction techniques: SparseNeuS [23], VolRecon [29], NeuSurf [15] and S-VolSDF [40]. These methods leverage MVS priors predominantly trained on multi-view datasets such as DTU [16], ensuring they operate within a similar data distribution. Additionally, we compare our approach with another point-based (dense-view) reconstruction method SuGaR [13] that employs Gaussians as the underlying 3D representation. To ensure a fair comparison, we initialize SuGaR [13] with point clouds obtained using DUSt3R [35], which improves its results. We also evaluate against surface reconstruction baselines directly from point clouds such as Poisson reconstruction [17], Points2Surf [9] and CAP-UDF [53], directly applied to the DUSt3R [35] point clouds. Further, we compare against dense volume rendering methods such as VolSDF [45] and NeuS [33].

Scan ID	21	24	34	37	38	40	82	106	110	114	118	Mean CD
Points2Surf [9]	3.73	2.85	2.55	5.13	3.85	2.41	2.30	3.95	3.33	2.37	2.84	3.21
DUSt3R [35] + Poiss. [17]	3.31	2.12	2.00	4.25	3.28	2.59	2.48	4.28	3.85	2.68	3.32	3.11
CAP-UDF [53]	2.72	1.53	1.45	4.05	2.78	1.81	4.22	3.51	3.83	2.24	3.65	2.89
NeuS [33]	4.52	3.33	3.03	4.77	1.87	4.35	1.89	4.18	5.46	1.09	2.40	3.36
VolSDF [45]	4.54	2.61	1.51	4.05	1.27	3.58	3.48	2.62	2.79	0.52	1.10	2.56
SuGar [13]	2.71	2.04	2.14	4.01	2.90	2.45	4.68	3.82	3.28	2.44	2.66	3.01
SparseNeus$_{ft}$ [23]	3.73	4.48	3.28	5.21	3.29	4.21	3.30	2.73	3.39	1.40	2.46	3.41
VolRecon [29]	3.05	3.30	2.27	4.36	2.51	3.24	3.30	3.10	3.58	1.86	3.68	3.11
S-VolSDF [40]	3.18	2.95	2.19	3.40	2.30	2.69	2.69	1.60	1.48	1.21	1.16	2.26
NeuSurf [15]	3.22	2.42	1.38	2.61	1.72	3.46	2.68	1.44	2.42	**0.61**	**0.87**	2.08
Ours	**2.36**	**1.12**	**0.83**	**2.39**	**1.14**	**1.55**	**1.67**	**1.26**	**1.14**	**0.61**	0.94	**1.36**

Table 1. **Quantitative mesh reconstruction comparison** based on Chamfer Distance (mm) ↓ on the DTU dataset. On average, we improve on the previous best method by **35%** (**1.36** vs. 2.08 CD). We also outperform various baselines that work on points only.

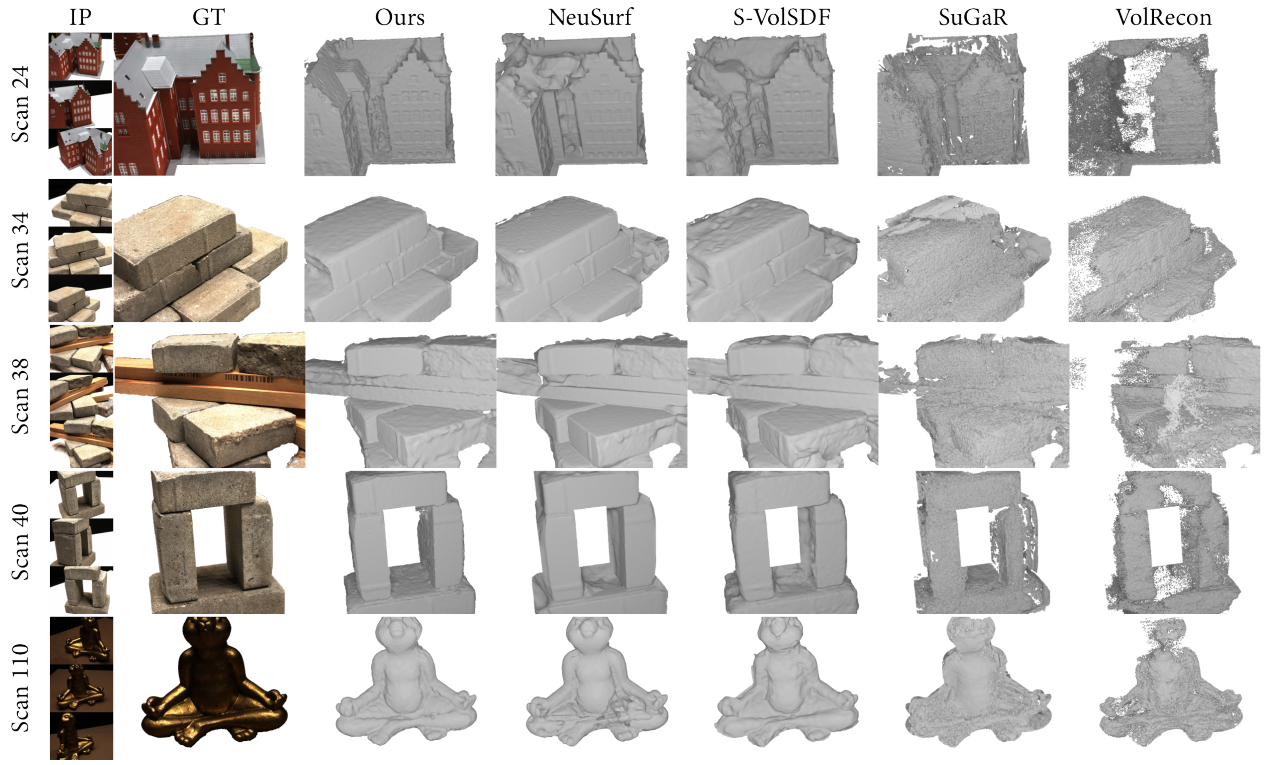

Figure 3. **Qualitative mesh reconstruction comparison on DTU**. Compared to previous state-of-the-art sparse-view methods, our reconstruction demonstrates superior completeness in regions with less view overlap. Our closest competitor is NeuSurf, which also reconstructs high quality surfaces on the object-centric DTU scenes. However, it fails to generalize to larger scenes (c.f. Fig. 5).

Metrics. We evaluate our technique against the baselines using both mesh reconstruction and novel view synthesis (NVS) metrics. For mesh quality assessment, we employ the Chamfer Distance (CD), which measures the accuracy of the reconstructed mesh by calculating the average distance between points sampled from the mesh and the corresponding points in the ground-truth point cloud. For NVS, we utilize Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Learned Perceptual Image Patch Similarity (LPIPS).

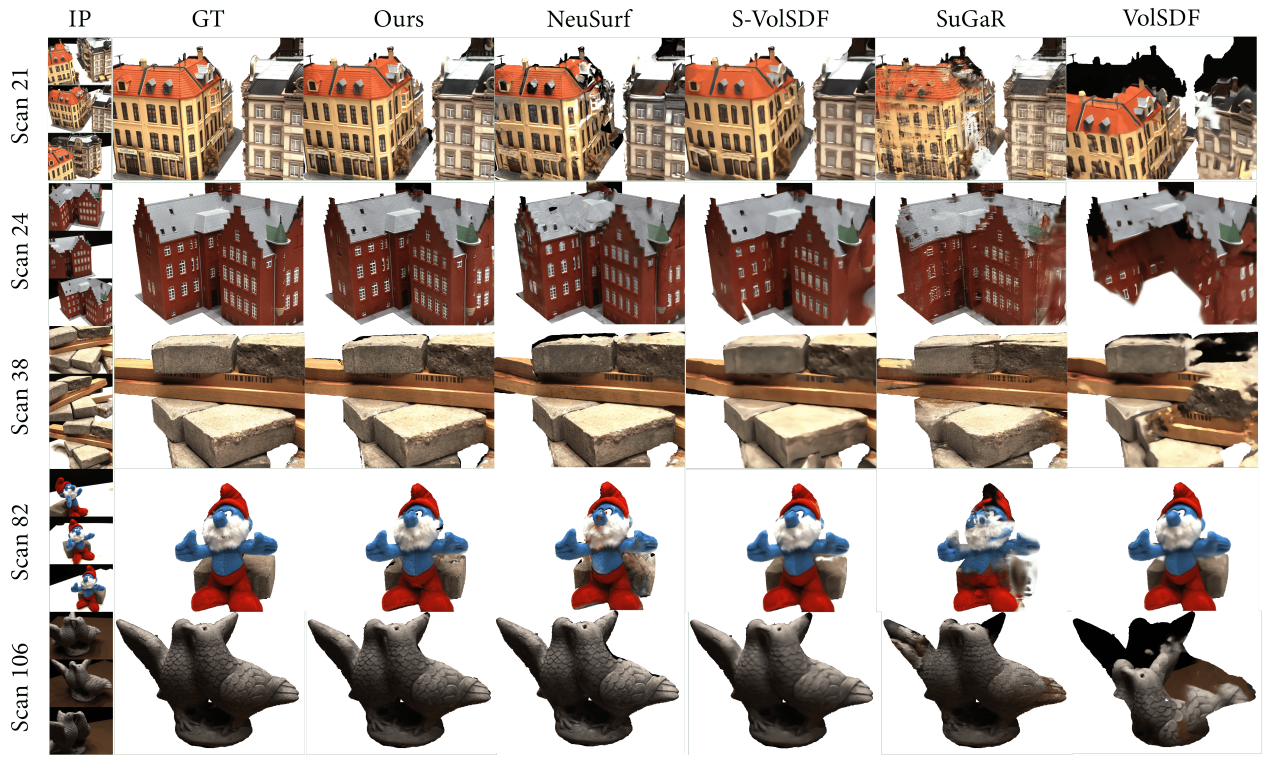

Figure 4. **Qualitative NVS comparison on DTU**. Our method demonstrates superior novel view synthesis quality relative to previous techniques. In comparison to NeuSurf [15] and S-VolSDF [40], our method produces sharper details. The Gaussian reconstruction method SuGaR [13] and volume rendering approach VolSDF [45] are not designed for sparse-view reconstruction and, therefore, show typical artifacts.

	PSNR ↑	SSIM ↑	LPIPS ↓
IBRNet$_{ft}$ [34]	15.71	0.75	0.29
MVSNeRF [6]	18.37	0.81	0.25
VolSDF [45]	14.18	0.62	0.35
S-VolSDF [40]	19.67	0.71	0.30
NeuSurf [15]	18.95	0.76	0.26
SuGaR [13]	**21.32**	**0.83**	0.24
Ours	20.78	0.80	**0.20**

Table 2. **Quantitative NVS comparison on DTU**. Our method reaches state-of-the-art novel view synthesis quality by being on par with SuGaR [13]. Note that SuGaR achieves much lower surface quality (c.f. Tab. 1) and shows artifacts in qualitative results (c.f. Fig. 4) in the given sparse-view setting.

Implementation Details. For the neural point representation, we built upon codebases from previous work [37, 44]. Our training process for the local prior utilizes a batch size of 5. Each batch instance comprises 40,000 randomly sampled query points, equally distributed w.r.t positive and negative signed distances, along with 2,000 neural points. We train the geometry networks and the latent codes for 5,000 epochs. The total training time for the local prior is approximately 8 hours, utilizing a single A100 GPU.

For sparse-view reconstruction, we optimize the parameters for 100,000 iterations using the Adam optimizer [19] on a single A100 GPU, which takes 3.5 hrs to converge depending upon the number of neural points. We refer to the supplementary material for more details.

5.1. Reconstruction Results

Our method demonstrates state-of-the-art quantitative results (Table 1) in comparison to previous sparse-view and point-based reconstruction techniques. Qualitative comparisons are presented in Figure 3 and the supplement. Our reconstructions exhibit superior completeness and absence of floaters, resulting in enhanced reconstruction quality. Notably, while previous works utilize DTU for prior training and inference on the same data distribution, our prior is trained exclusively on synthetic data (Section 4.2). Leveraging our local property, we evaluate our method on unbounded scenes from Mip-NeRF360. Figure 5 presents qualitative mesh comparison results with NeuSurf [15], illustrating that our method achieves significantly more accurate reconstructions. In the absence of ground-truth point

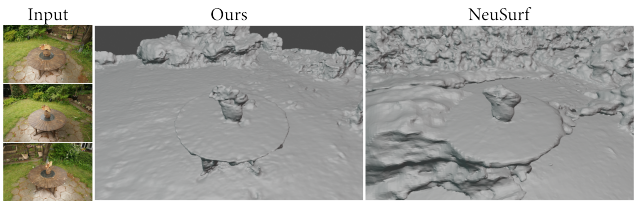

Figure 5. **Qualitative mesh reconstruction comparison on Mip-NeRF360 [2]**. While NeuSurf [15] also produces good results on object-centric scenes it fails on larger, unbounded scenes. In contrast, our local prior generalizes well to Mip-NeRF360. Please refer to the appendix for additional results.

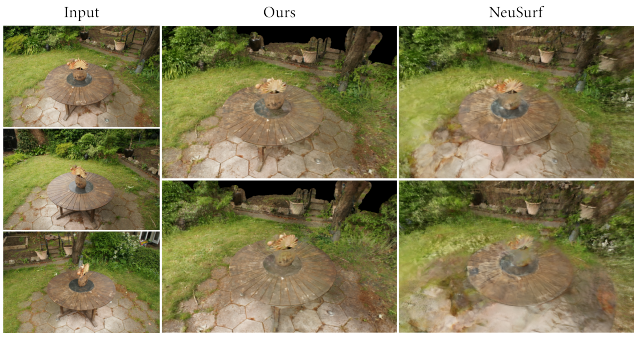

Figure 6. **Qualitative NVS comparison on Mip-NeRF360 [2]**. Our geometry prior acts as effective regularization for appearance resulting in robust fitting of sparse views. Novel views from NeuSurf [15] quickly deteriorate when moving away from training views, indicating overfitting.

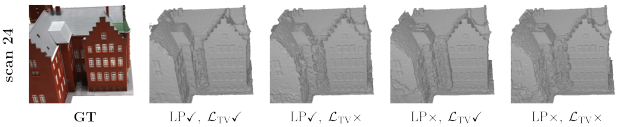

Figure 7. **Qualitative ablation** of our local prior (LP) and total variation $\mathcal{L}_{\text{TV}}$ regularization of geometry latent codes. It can be seen that both improve surface quality.

clouds, our evaluation is limited to qualitative comparisons with more results in the supplementary material.

Quantitative and qualitative results for novel view synthesis are presented in Table 2, Figure 4 for DTU and Figure 6 for Mip-Nerf360, respectively. Our method achieves state-of-the-art NVS results among volume rendering-based techniques. The results are comparable to the Gaussian splatting-based SuGaR [13], despite SuGaR's inferior surface reconstruction quality.

5.2. Ablation Study

We study the effect of our proposed local prior and the total variation regularization $\mathcal{L}_{\text{TV}}$ of the geometry latent codes with quantitative results in Table 3 and qualitative results in Figure 7. With the proposed point-based representation and regularizing losses from prior works (cf. Section 4.3), Spurfies matches the performance of the state-of-the-art baseline NeuSurf [15]. Leveraging the local prior obtained by training on synthetic data significantly enhances the level of detail in reconstructions. The total variation regularization on top mainly removes noise in under-constrained regions resulting in clean meshes.

Local Prior	$\mathcal{L}_{\text{TV}}$	**Mean CD** ↓
×	×	2.09
×	✓	1.91
✓	×	1.59
✓	✓	**1.36**

Table 3. **Quantitative ablation** of the proposed local prior and total variation regularization of geometry latent codes. Both contribute strongly to the reconstruction quality.

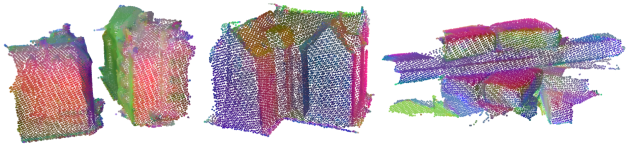

Figure 8. **Learned geometry latent codes** visualized via PCA. We observe similar features for points with same surface orientations.

Analysis. In Figure 8, we visualize the learned geometry latent codes using Principal Component Analysis (PCA). It reveals a correlation between similar orientations and their corresponding geometry codes. By clustering the points based on their learnt latent codes we can also extract parts that are similarly oriented (c.f. supplementary material).

6. Conclusion

We introduced Spurfies, a novel approach for sparse-view surface reconstruction that uses a distributed neural representation on point clouds and completely disentangles geometry and appearance. Our work shows that using a small subset of accurate synthetic ShapeNet data is sufficient to learn a high-quality local surface prior. We evaluated our method on the DTU and Mip-NeRF360 datasets, demonstrating state-of-the-art performance in mesh reconstruction from sparse views on DTU and that our method does generalize to large scenes. Our results indicate that Spurfies effectively mitigates the shape-radiance ambiguity inherent in sparse-view settings, producing high-quality surface reconstructions with sparse input views. Our work provides an important insight for the future direction of the field, which is that the geometry prior is most important and can effectively be modeled by disentangling it from appearance and by training it on synthetic data.

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