Neuralangelo: High-Fidelity Neural Surface Reconstruction

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https://research.nvidia.com/labs/dir/neuralangelo

Figure 1. We present **Neuralangelo**, a framework for high-fidelity 3D surface reconstruction from RGB images using neural volume rendering, even without auxiliary data such as segmentation or depth. Shown in the figure is an extracted 3D mesh of a courthouse.

Abstract

Neural surface reconstruction has been shown to be powerful for recovering dense 3D surfaces via image-based neural rendering. However, current methods struggle to recover detailed structures of real-world scenes. To address the issue, we present ***Neuralangelo****, which combines the representation power of multi-resolution 3D hash grids with neural surface rendering. Two key ingredients enable our approach: (1) numerical gradients for computing higher-order derivatives as a smoothing operation and (2) coarse-to-fine optimization on the hash grids controlling different levels of details. Even without auxiliary inputs such as depth, Neuralangelo can effectively recover dense 3D surface structures from multi-view images with fidelity significantly surpassing previous methods, enabling detailed large-scale scene reconstruction from RGB video captures.*

1. Introduction

3D surface reconstruction aims to recover dense geometric scene structures from multiple images observed at different viewpoints [9]. The recovered surfaces provide structural information useful for many downstream applications, such as 3D asset generation for augmented/virtual/mixed reality or environment mapping for autonomous navigation of robotics. Photogrammetric surface reconstruction using a monocular RGB camera is of particular interest, as it equips users with the capability of casually creating digital twins of the real world using ubiquitous mobile devices.

Classically, multi-view stereo algorithms [6, 16, 29, 34] had been the method of choice for sparse 3D reconstruction. An inherent drawback of these algorithms, however, is their inability to handle ambiguous observations, *e.g.* regions with large areas of homogeneous colors, repetitive texture

patterns, or strong color variations. This would result in inaccurate reconstructions with noisy or missing surfaces. Recently, neural surface reconstruction methods [36, 41, 42] have shown great potential in addressing these limitations. This new class of methods uses coordinate-based multi-layer perceptrons (MLPs) to represent the scene as an implicit function, such as occupancy fields [25] or signed distance functions (SDF) [36, 41, 42]. Leveraging the inherent continuity of MLPs and neural volume rendering [22], these techniques allow the optimized surfaces to meaningfully interpolate between spatial locations, resulting in smooth and complete surface representations.

Despite the superiority of neural surface reconstruction methods over classical approaches, the recovered fidelity of current methods does not scale well with the capacity of MLPs. Recently, Müller *et al*. [23] proposed a new scalable representation, referred to as Instant NGP (Neural Graphics Primitives). Instant NGP introduces a hybrid 3D grid structure with a multi-resolution hash encoding and a lightweight MLP that is more expressive with a memory footprint log-linear to the resolution. The proposed hybrid representation greatly increases the representation power of neural fields and has achieved great success at representing very fine-grained details for a wide variety of tasks, such as object shape representation and novel view synthesis problems.

In this paper, we propose **Neuralangelo** for high-fidelity surface reconstruction (Fig. 1). Neuralangelo adopts Instant NGP as a neural SDF representation of the underlying 3D scene, optimized from multi-view image observations via neural surface rendering [36]. We present two findings central to fully unlocking the potentials of multi-resolution hash encodings. First, using *numerical* gradients to compute higher-order derivatives, such as surface normals for the eikonal regularization [8, 12, 20, 42], is critical to stabilizing the optimization. Second, a *progressive* optimization schedule plays an important role in recovering the structures at different levels of details. We combine these two key ingredients and, via extensive experiments on standard benchmarks and real-world scenes, demonstrate significant improvements over image-based neural surface reconstruction methods in *both* reconstruction accuracy and view synthesis quality.

In summary, we present the following contributions:

- We present the Neuralangelo framework to naturally incorporate the representation power of multi-resolution hash encoding [23] into neural SDF representations.
- We present two simple techniques to improve the quality of hash-encoded surface reconstruction: higher-order derivatives with numerical gradients and coarse-to-fine optimization with a progressive level of details.
- We empirically demonstrate the effectiveness of Neuralangelo on various datasets, showing significant improvements over previous methods.

2. Related work

Multi-view surface reconstruction. Early image-based photogrammetry techniques use a volumetric occupancy grid to represent the scene [4, 16, 17, 29, 32]. Each voxel is visited and marked occupied if strict color constancy between the corresponding projected image pixels is satisfied. The photometric consistency assumption typically fails due to auto-exposure or non-Lambertian materials, which are ubiquitous in the real world. Relaxing such color constancy constraints across views is important for realistic 3D reconstruction.

Follow-up methods typically start with 3D point clouds from multi-view stereo techniques [6, 7, 28, 34] and then perform dense surface reconstruction [13, 14]. Reliance on the quality of the generated point clouds often leads to missing or noisy surfaces. Recent learning-based approaches augment the point cloud generation process with learned image features and cost volume construction [2, 10, 40]. However, these approaches are inherently limited by the resolution of the cost volume and fail to recover geometric details.

Neural Radiance Fields (NeRF). NeRF [22] achieves remarkable photorealistic view synthesis with view-dependent effects. NeRF encodes 3D scenes with an MLP mapping 3D spatial locations to color and volume density. These predictions are composited into pixel colors using neural volume rendering. A problem of NeRF and its variants [1, 30, 43, 46], however, is the question of how an isosurface of the volume density could be defined to represent the underlying 3D geometry. Current practice often relies on heuristic thresholding on the density values; due to insufficient constraints on the level sets, however, such surfaces are often noisy and may not model the scene structures accurately [36, 41]. Therefore, more direct modeling of surfaces is preferred for photogrammetric surface reconstruction problems.

Neural surface reconstruction. For scene representations with better-defined 3D surfaces, implicit functions such as occupancy grids [24, 25] or SDFs [42] are preferred over simple volume density fields. To integrate with neural volume rendering [22], different techniques [36, 41] have been proposed to reparametrize the underlying representations back to volume density. These designs of neural implicit functions enable more accurate surface prediction with view synthesis capabilities of unsacrificed quality [42].

Follow-up works extend the above approaches to real-time at the cost of surface fidelity [18, 37], while others [3, 5, 44] use auxiliary information to enhance the reconstruction results. Notably, NeuralWarp [3] uses patch warping given co-visibility information from structure-from-motion (S*f*M) to guide surface optimization, but the patch-wise planar assumption fails to capture highly-varying surfaces [3]. Other methods [5, 45] utilize sparse point clouds from S*f*M to supervise the SDF, but their performances are upper-bounded by the quality of the point clouds, as with

classical approaches [45]. The use of monocular depth and segmentation as auxiliary data has also been explored with unconstrained image collections [31] or using scene representations with hash encodings [44]. In contrast, our work Neuralangelo builds upon hash encodings [23] to recover surfaces but *without* the need for auxiliary inputs used in prior work [3, 5, 31, 44, 45]. Concurrent work [38] also proposes coarse-to-fine optimization for improved surface details, where a displacement network corrects the shape predicted by a coarse network. In contrast, we use hierarchical hash grids and control the level of details based on our analysis of higher-order derivatives.

3. Approach

Neuralangelo reconstructs dense structures of the scene from multi-view images. Neuralangelo samples 3D locations along camera view directions and uses a multi-resolution hash encoding to encode the positions. The encoded features are input to an SDF MLP and a color MLP to composite images using SDF-based volume rendering.

3.1. Preliminaries

Neural volume rendering. NeRF [22] represents a 3D scene as volume density and color fields. Given a posed camera and a ray direction, the volume rendering scheme integrates the color radiance of sampled points along the ray. The i-th sampled 3D position $\mathbf{x}_i$ is at a distance t_i from the camera center. The volume density σ_i and color $\mathbf{c}_i$ of each sampled point are predicted using a coordinate MLP. The rendered color of a given pixel is approximated as the Riemann sum:

$$\hat{\mathbf{c}}(\mathbf{o},\mathbf{d}) = \sum_{i=1}^{N} w_i \mathbf{c}_i, \quad \text{where } w_i = T_i \alpha_i. \tag{1}$$

Here, $\alpha_i = 1 - \exp(-\sigma_i \delta_i)$ is the opacity of the i-th ray segment, $\delta_i = t_{i+1} - t_i$ is the distance between adjacent samples, and $T_i = \Pi_{j=1}^{i-1}(1-\alpha_j)$ is the accumulated transmittance, indicating the fraction of light that reaches the camera. To supervise the network, a color loss is used between input images $\mathbf{c}$ and rendered images $\hat{\mathbf{c}}$:

$$\mathcal{L}_{\text{RGB}} = \|\hat{\mathbf{c}} - \mathbf{c}\|_1 . \tag{2}$$

However, surfaces are not clearly defined using such density formulation. Extracting surfaces from density-based representation often leads to noisy and unrealistic results [36, 41].

Volume rendering of SDF. One of the most common surface representations is SDF. The surface $\mathcal{S}$ of an SDF can be implicitly represented by its zero-level set, *i.e.*, $\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^3 | f(\mathbf{x}) = 0\}$, where $f(\mathbf{x})$ is the SDF value. In the context of neural SDFs, Wang *et al.* [36] proposed to convert volume density predictions in NeRF to SDF representations with a logistic function to allow optimization with neural volume rendering. Given a 3D point $\mathbf{x}_i$ and SDF value $f(\mathbf{x}_i)$, the corresponding opacity value α_i used in Eq. 1 is computed as

$$\alpha_i = \max\left(\frac{\Phi_s(f(\mathbf{x}_i)) - \Phi_s(f(\mathbf{x}_{i+1}))}{\Phi_s(f(\mathbf{x}_i))}, 0\right), \tag{3}$$

where Φ_s is the sigmoid function. In this work, we use the same SDF-based volume rendering formulation [36].

Multi-resolution hash encoding. Recently, multi-resolution hash encoding proposed by Müller *et al.* [23] has shown great scalability for neural scene representations, generating fine-grained details for tasks such as novel view synthesis. In Neuralangelo, we adopt the representation power of hash encoding to recover high-fidelity surfaces.

The hash encoding uses multi-resolution grids, with each grid cell corner mapped to a hash entry. Each hash entry stores the encoding feature. Let $\{V_1, ..., V_L\}$ be the set of different spatial grid resolutions. Given an input position $\mathbf{x}_i$, we map it to the corresponding position at each grid resolution V_l as $\mathbf{x}_{i,l} = \mathbf{x}_i \cdot V_l$. The feature vector $\gamma_l(\mathbf{x}_{i,l}) \in \mathbb{R}^c$ given resolution V_l is obtained via trilinear interpolation of hash entries at the grid cell corners. The encoding features across all spatial resolutions are concatenated together, forming a $\gamma(\mathbf{x}_i) \in \mathbb{R}^{cL}$ feature vector:

$$\gamma(\mathbf{x}_i) = \big(\gamma_1(\mathbf{x}_{i,1}), ..., \gamma_L(\mathbf{x}_{i,L})\big). \tag{4}$$

The encoded features are then passed to a shallow MLP.

One alternative to hash encoding is sparse voxel structures [30, 33, 39, 43], where each grid corner is uniquely defined without collision. However, volumetric feature grids require hierarchical spatial decomposition (*e.g.* octrees) to make the parameter count tractable; otherwise, the memory would grow cubically with spatial resolution. Given such hierarchy, finer voxel resolutions by design cannot recover surfaces that are misrepresented by the coarser resolutions [33]. Hash encoding instead assumes no spatial hierarchy and resolves collision automatically based on gradient averaging [23].

3.2. Numerical Gradient Computation

We show in this section that the analytical gradient w.r.t. position of hash encoding suffers from localities. Therefore, optimization updates only propagate to local hash grids, lacking non-local smoothness. We propose a simple fix to such a locality problem by using numerical gradients. An overview is shown in Fig. 2.

A special property of SDF is its differentiability with a gradient of the unit norm. The gradient of SDF satisfies the eikonal equation $\|\nabla f(\mathbf{x})\|_2 = 1$ (almost everywhere). To enforce the optimized neural representation to be a valid SDF, the eikonal loss [8] is typically imposed on the SDF predictions:

$$\mathcal{L}_{\text{eik}} = \frac{1}{N}\sum_{i=1}^{N}(\|\nabla f(\mathbf{x}_i)\|_2 - 1)^2, \tag{5}$$

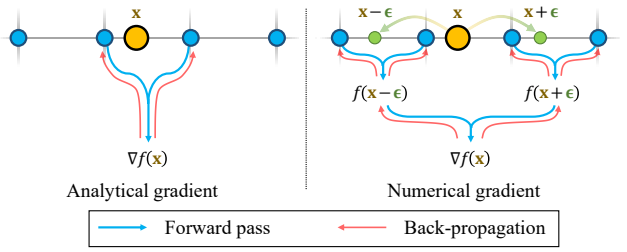


Figure 2. Using **numerical gradients** for higher-order derivatives distributes the back-propagation updates beyond the local hash grid cell, thus becoming a smoothed version of **analytical gradients**.

where N is the total number of sampled points. To allow for end-to-end optimization, a double backward operation on the SDF prediction $f(\mathbf{x})$ is required.

The *de facto* method for computing surface normals of SDFs $\nabla f(\mathbf{x})$ is to use analytical gradients [36, 41, 42]. Analytical gradients of hash encoding w.r.t. position, however, are *not* continuous across space under trilinear interpolation. To find the sampling location in a voxel grid, each 3D point $\mathbf{x}_i$ would first be scaled by the grid resolution V_l, written as $\mathbf{x}_{i,l} = \mathbf{x}_i \cdot V_l$. Let the coefficient for (tri-)linear interpolation be $\beta = \mathbf{x}_{i,l} - \lfloor \mathbf{x}_{i,l} \rfloor$. The resulting feature vectors are

$$\gamma_l(\mathbf{x}_{i,l}) = \gamma_l(\lfloor \mathbf{x}_{i,l} \rfloor) \cdot (1-\beta) + \gamma_l(\lceil \mathbf{x}_{i,l} \rceil) \cdot \beta, \quad (6)$$

where the rounded position $\lfloor \mathbf{x}_{i,l} \rfloor, \lceil \mathbf{x}_{i,l} \rceil$ correspond to the local grid cell corners. We note that rounding operations $\lfloor \cdot \rfloor$ and $\lceil \cdot \rceil$ are non-differentiable. As a result, the derivative of hash encoding w.r.t. the position can be obtained as

$$\begin{aligned} \frac{\partial \gamma_l(\mathbf{x}_{i,l})}{\partial \mathbf{x}_i} &= \gamma_l(\lfloor \mathbf{x}_{i,l} \rfloor) \cdot (-\frac{\partial \beta}{\partial \mathbf{x}_{i,l}}) + \gamma_l(\lceil \mathbf{x}_{i,l} \rceil) \cdot \frac{\partial \beta}{\partial \mathbf{x}_{i,l}} \\ &= \gamma_l(\lfloor \mathbf{x}_{i,l} \rfloor) \cdot (-V_l) + \gamma_l(\lceil \mathbf{x}_{i,l} \rceil) \cdot V_l \ . \end{aligned} \quad (7)$$

The derivative of hash encoding is local, *i.e.*, when $\mathbf{x}_i$ moves across grid cell borders, the corresponding hash entries will be different. Therefore, the eikonal loss defined in Eq. 5 only back-propagates to the locally sampled hash entries, *i.e.* $\gamma_l(\lfloor \mathbf{x}_{i,l} \rfloor)$ and $\gamma_l(\lceil \mathbf{x}_{i,l} \rceil)$. When continuous surfaces (*e.g.* a flat wall) span multiple grid cells, these grid cells should produce coherent surface normals without sudden transitions. To ensure consistency in surface representation, joint optimization of these grid cells is desirable. However, the analytical gradient is limited to local grid cells, unless all corresponding grid cells happen to be sampled and optimized simultaneously. Such sampling is not always guaranteed.

To overcome the locality of the analytical gradient of hash encoding, we propose to compute the surface normals using *numerical* gradients. If the step size of the numerical gradient is smaller than the grid size of hash encoding, the numerical gradient would be equivalent to the analytical gradient; otherwise, hash entries of multiple grid cells would participate in the surface normal computation. Back-propagating through the surface normals thus allows hash entries of multiple grids to receive optimization updates simultaneously. Intuitively, numerical gradients with carefully chosen step sizes can be interpreted as a smoothing operation on the analytical gradient expression. An alternative of normal supervision is a teacher-student curriculum [35, 47], where the predicted noisy normals are driven towards MLP outputs to exploit the smoothness of MLPs. However, analytical gradients from such teacher-student losses still only back-propagate to local grid cells for hash encoding. In contrast, numerical gradients solve the locality issue without the need of additional networks.

To compute the surface normals using the numerical gradient, additional SDF samples are needed. Given a sampled point $\mathbf{x}_i = (x_i, y_i, z_i)$, we additionally sample two points along each axis of the canonical coordinate around x_i within a vicinity of a step size of ϵ. For example, the x-component of the surface normal can be found as

$$\nabla_x f(\mathbf{x}_i) = \frac{f\left(\gamma(\mathbf{x}_i + \boldsymbol{\epsilon}_x)\right) - f\left(\gamma(\mathbf{x}_i - \boldsymbol{\epsilon}_x)\right)}{2\epsilon}, \quad (8)$$

where $\boldsymbol{\epsilon}_x = [\epsilon, 0, 0]$. In total, six additional SDF samples are required for numerical surface normal computation.

3.3. Progressive Levels of Details

Coarse-to-fine optimization can better shape the loss landscape to avoid falling into false local minima. Such a strategy has found many applications in computer vision, such as image-based registration [19, 21, 26]. Neuralangelo also adopts a coarse-to-fine optimization scheme to reconstruct the surfaces with progressive levels of details. Using numerical gradients for the higher-order derivatives naturally enables Neuralangelo to perform coarse-to-fine optimization from two perspectives.

Step size ϵ. As previously discussed, numerical gradients can be interpreted as a smoothing operation where the step size ϵ controls the resolution and the amount of recovered details. Imposing $\mathcal{L}_{\text{eik}}$ with a larger ϵ for numerical surface normal computation ensures the surface normal is consistent at a larger scale, thus producing consistent and continuous surfaces. On the other hand, imposing $\mathcal{L}_{\text{eik}}$ with a smaller ϵ affects a smaller region and avoids smoothing details. In practice, we initialize the step size ϵ to the coarsest hash grid size and exponentially decrease it matching different hash grid sizes throughout the optimization process.

Hash grid resolution V. If all hash grids are activated from the start of the optimization, to capture geometric details, fine hash grids must first "unlearn" from the coarse optimization with large step size ϵ and "relearn" with a smaller ϵ. If such a process is unsuccessful due to converged optimization, geometric details would be lost. Therefore, we only enable an initial set of coarse hash grids and progressively activate

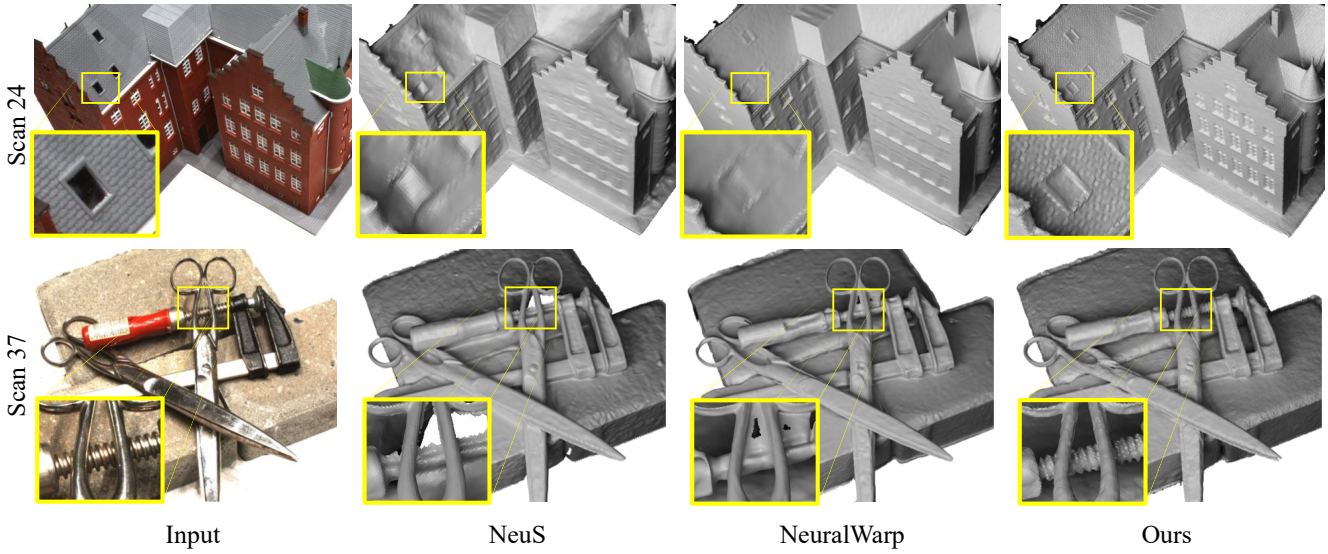


Figure 3. **Qualitative comparison on the DTU benchmark [11].** Neuralangelo produces more accurate and higher-fidelity surfaces.

finer hash grids throughout optimization when ϵ decreases to their spatial size. The relearning process can thus be avoided to better capture the details. In practice, we also apply weight decay over all parameters to avoid single-resolution features dominating the final results.

3.4. Optimization

To further encourage the smoothness of the reconstructed surfaces, we impose a prior by regularizing the mean curvature of SDF. The mean curvature is computed from discrete Laplacian similar to the surface normal computation, otherwise, the second-order analytical gradients of hash encoding are zero everywhere when using trilinear interpolation. The curvature loss $\mathcal{L}_{\text{curv}}$ is defined as:

$$\mathcal{L}_{\text{curv}} = \frac{1}{N}\sum_{i=1}^{N}\left|\nabla^2 f(\mathbf{x}_i)\right| . \tag{9}$$

We note that the samples used for the surface normal computation in Eq. 8 are sufficient for curvature computation.

The total loss is defined as the weighted sum of losses:

$$\mathcal{L} = \mathcal{L}_{\text{RGB}} + w_{\text{eik}}\mathcal{L}_{\text{eik}} + w_{\text{curv}}\mathcal{L}_{\text{curv}} . \tag{10}$$

All network parameters, including MLPs and hash encoding, are trained jointly end-to-end.

4. Experiments

Datasets. Following prior work, we conduct experiments on 15 object-centric scenes of the DTU dataset [11]. Each scene has 49 or 64 images captured by a robot-held monocular RGB camera. The ground truth is obtained from a structured-light scanner. We further conduct experiments on 6 scenes of the Tanks and Temples dataset [15], including large-scale indoor/outdoor scenes. Each scene contains 263 to 1107 images captured using a hand-held monocular RGB camera. The ground truth is obtained using a LiDAR sensor.

Implementation details. Our hash encoding resolution spans 2^5 to 2^{11} with 16 levels. Each hash entry has a channel size of 8. The maximum number of hash entries of each resolution is 2^{22}. We activate 4 and 8 hash resolutions at the beginning of optimization for DTU dataset and Tanks and Temples respectively, due to differences in scene scales. We enable a new hash resolution every 5000 iterations when the step size ϵ equals its grid cell size. For all experiments, we do *not* utilize auxiliary data such as segmentation or depth during the optimization process.

Evaluation criteria. We report Chamfer distance and F1 score for surface evaluation [11, 15]. We use peak signal-to-noise ratio (PSNR) to report image synthesis qualities.

4.1. DTU Benchmark

We show qualitative results in Fig. 3 and quantitative results in Table 1. On average, Neuralangelo achieves the lowest Chamfer distance and the highest PSNR, even without using auxiliary inputs. The result suggests that Neuralangelo is more generally applicable than prior work when recovering surfaces and synthesizing images, despite not performing best in every individual scene.

We further ablate Neuralangelo against the following conditions: 1) AG: analytical gradients, 2) AG+P: analytical gradients and progressive activating hash resolutions, 3) NG: numerical gradients with varying ϵ. Fig. 4 shows the results qualitatively. AG produces noisy surfaces, even with hash resolutions progressively activated (AG+P). NG improves

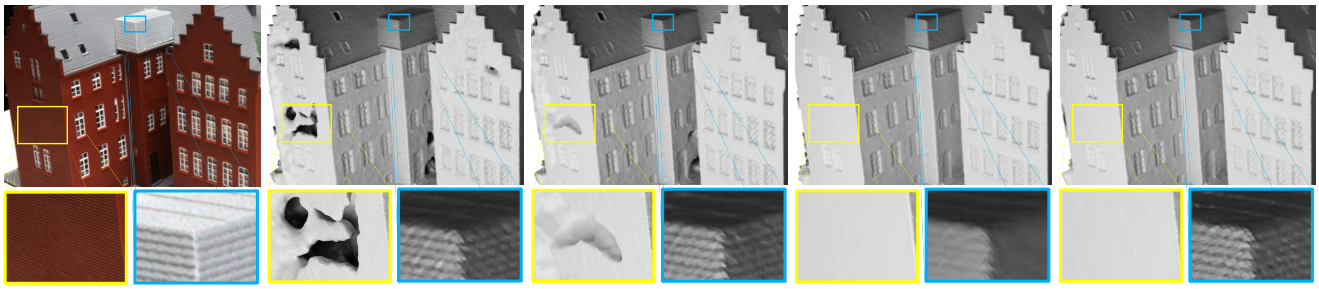


Figure 4. **Qualitative comparison of different coarse-to-fine optimization scheme.** When using the analytical gradient (AG and AG+P), coarse surfaces often contain artifacts. While using numerical gradients (NG) leads to a better coarse shape, details are also smoothed. Our solution (NG+P) produces both smooth surfaces and fine details.

		24	37	40	55	63	65	69	83	97	105	106	110	114	118	122	Mean
Chamfer distance (mm) ↓	NeRF [22]	1.90	1.60	1.85	0.58	2.28	1.27	1.47	1.67	2.05	1.07	0.88	2.53	1.06	1.15	0.96	1.49
	VolSDF [41]	1.14	1.26	0.81	0.49	1.25	0.70	0.72	1.29	1.18	0.70	0.66	1.08	0.42	0.61	0.55	0.86
	NeuS [36]	1.00	1.37	0.93	0.43	1.10	0.65	**0.57**	1.48	1.09	0.83	0.52	1.20	0.35	0.49	0.54	0.84
	HF-NeuS [38]	0.76	1.32	0.70	0.39	1.06	0.63	0.63	**1.15**	1.12	0.80	0.52	1.22	0.33	0.49	0.50	0.77
	RegSDF [45] †	0.60	1.41	0.64	0.43	1.34	**0.62**	0.60	**0.90**	**0.92**	1.02	0.60	**0.59**	**0.30**	**0.41**	**0.39**	0.72
	NeuralWarp [3] †	0.49	**0.71**	**0.38**	0.38	**0.79**	0.81	0.82	1.20	1.06	**0.68**	0.66	**0.74**	0.41	0.63	0.51	0.68
	AG	0.67	1.04	0.84	0.39	1.43	1.23	1.11	1.24	1.54	0.85	0.50	1.01	0.37	0.51	0.44	0.88
	AG+P	0.59	0.95	0.46	**0.34**	1.19	0.70	0.79	1.19	1.37	**0.69**	**0.49**	0.93	0.33	**0.44**	0.44	0.73
	NG	**0.48**	0.81	0.43	**0.35**	0.89	0.71	0.61	1.26	1.06	0.74	**0.47**	0.79	0.33	0.45	**0.43**	**0.65**
	NG+P (Ours)	**0.37**	**0.72**	**0.35**	**0.35**	**0.87**	**0.54**	**0.53**	1.29	**0.97**	0.73	**0.47**	**0.74**	**0.32**	**0.41**	**0.43**	**0.61**
PSNR ↑	RegSDF [45] †	24.78	23.06	23.47	22.21	28.57	25.53	21.81	28.89	26.81	27.91	24.71	25.13	26.84	21.67	28.25	25.31
	NeuS [36]	26.62	23.64	26.43	25.59	30.61	**32.83**	29.24	33.71	26.85	31.97	32.18	28.92	28.41	35.00	34.81	29.79
	VolSDF [41]	26.28	25.61	26.55	26.76	31.57	31.50	29.38	33.23	28.03	32.13	33.16	31.49	30.33	34.90	34.75	30.38
	NeRF [22]	26.24	**25.74**	26.79	27.57	**31.96**	31.50	29.58	32.78	**28.35**	32.08	33.49	**31.54**	**31.00**	35.59	35.51	30.65
	AG	29.97	24.98	23.11	30.27	30.60	31.27	29.27	34.22	27.47	33.09	33.85	29.98	29.41	35.69	35.11	30.55
	AG+P	30.12	24.63	29.59	30.29	31.60	32.04	**29.85**	34.19	27.82	33.23	33.95	29.15	29.44	35.99	35.67	31.17
	NG	**30.34**	25.14	**30.20**	**30.79**	31.72	31.86	29.81	**34.36**	28.01	**33.45**	**34.38**	30.39	29.88	**36.02**	**35.74**	**31.47**
	NG+P (Ours)	**30.64**	**27.78**	**32.70**	**34.18**	**35.15**	**35.89**	**31.47**	**36.82**	**30.13**	**35.92**	**36.61**	**32.60**	**31.20**	**38.41**	**38.05**	**33.84**

Table 1. **Quantitative results on DTU dataset [11].** Neuralangelo achieves the best reconstruction accuracy and image synthesis quality. **Best result**. **Second best result**. † Requires 3D points from S*f*M. Best viewed in color.

the smoothness of the surface, sacrificing details. Our setup (NG+P) produces both smooth surfaces and fine details.

4.2. Tanks and Temples

As no public result is available for Tanks and Temples, we train NeuS [36] and NeuralWarp [3] following our setup. We also report classical multi-view stereo results using COLMAP [27]. As COLMAP and NeuralWarp do not support view synthesis, we only report PSNR from NeuS. Results are summarized in Fig. 5 and Table 2.

Neuralangelo achieves the highest average PSNR and performs best in terms of F1 score. Comparing against NeuS [36], we can recover high-fidelity surfaces with intricate details. We find that the dense surfaces generated from COLMAP are sensitive to outliers in the sparse point cloud. We also find that NeuralWarp often predicts surfaces for the sky and backgrounds potentially due to their color rendering scheme following VolSDF [41]. The additional surfaces predicted for backgrounds are counted as outliers and worsen F1 scores significantly. We instead follow NeuS [36] and use an additional network [46] to model the background.

Similar to the DTU results, using the analytical gradient produces noisy surfaces and thus leads to a low F1 score. We further note that the reconstruction of Courthouse shown in Figs. 1 and 5 are the same building of different sides, demonstrating the capability of Neuralangelo for large-scale granular reconstruction.

4.3. Level of Details

As Neuralangelo progressively optimizes the hash features of increasing resolution, we inspect the progressive level of details similar to NGLOD [33]. We show a qualitative visualization in Fig. 6. While some surfaces are entirely missed by coarse levels, for example, the tree, table, and

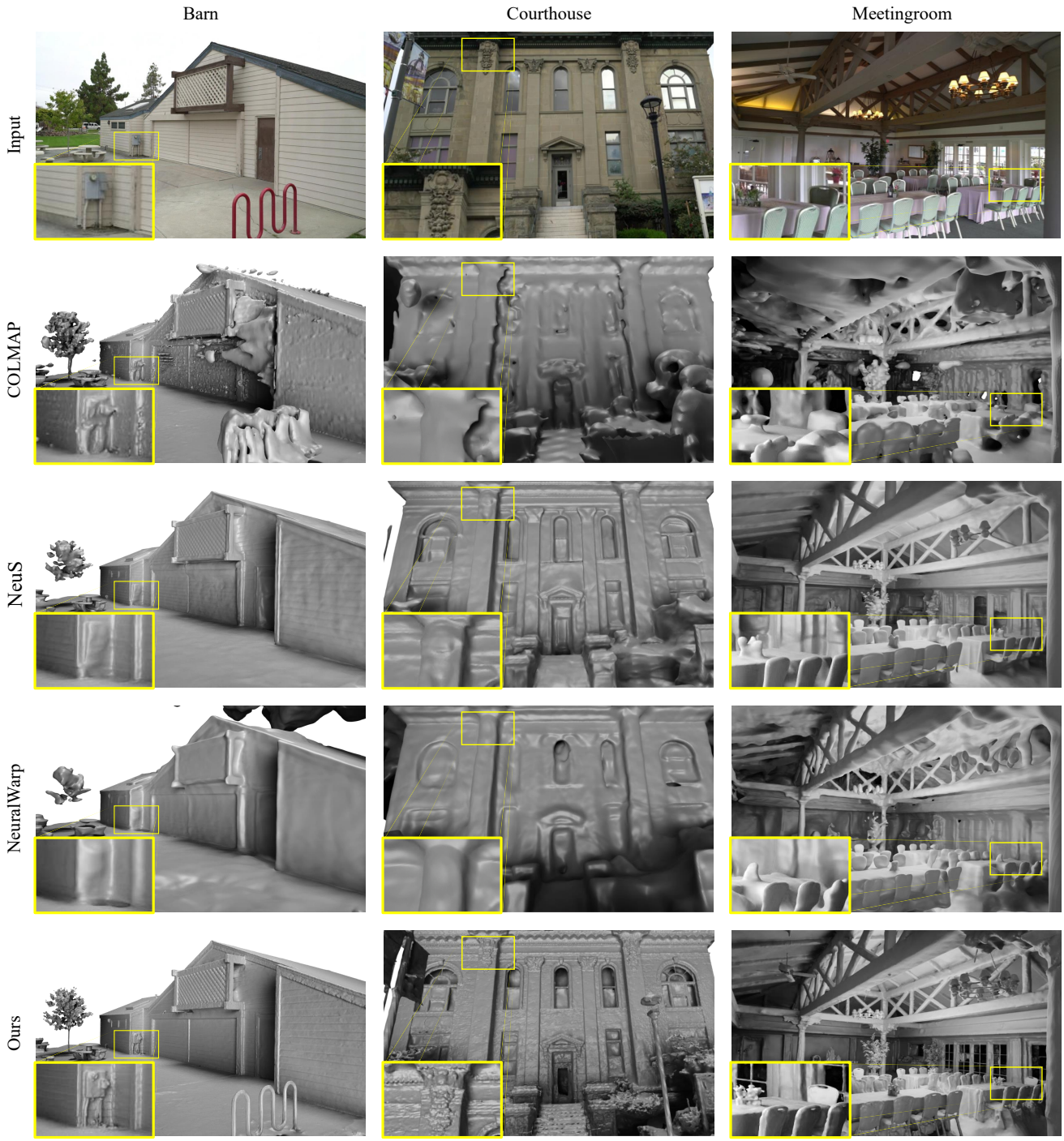
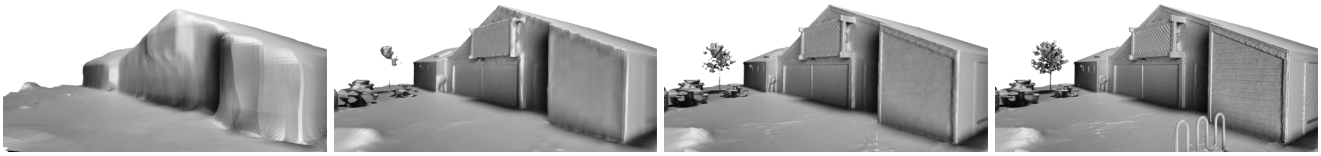


Figure 5. **Qualitative comparison on Tanks and Temples dataset [15].** Neuralangelo captures the scene details better compared to other baseline approaches, while baseline approaches have missing or noisy surfaces.

bike rack, these structures are recovered by finer resolutions successfully. The ability to recover missing surfaces demonstrates the advantages of our spatial hierarchy-free design.

Moreover, we note that flat surfaces are predicted at sufficiently high resolutions (around Level 8 in this example). Thus, only relying on the continuity of local cells of coarse resolutions is not sufficient to reconstruct large continuous surfaces. The result motivates the use of the numerical gradients for the higher-order derivatives, such that back-propagation is beyond local grid cells.

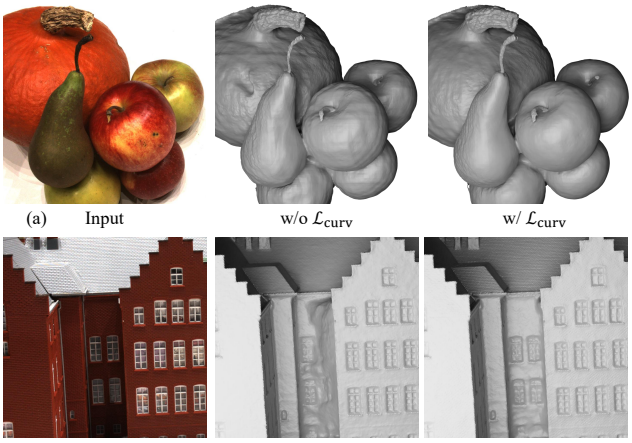


Level 4, V_4 =74 | Level 8, V_8 =223 | Level 12, V_{12} =676 | Level 16, V_{16} = 2048

Figure 6. **Results at different hash resolutions.** While some structures, such as the tree, table, and bike rack, are missed at coarse resolutions (Level 4). Finer resolutions can progressively recover these missing surfaces. Flat continuous surfaces also require sufficiently fine resolutions to predict (Level 8). The result motivates the non-local updates when using numerical gradients for higher-order derivatives.

	F1 Score ↑							PSNR ↑				
	NeuralWarp [3]	COLMAP [27]	NeuS [36]	AG	AG+P	NG	NG+P (Ours)	NeuS [36]	AG	AG+P	NG	NG+P (Ours)
Barn	0.22	0.55	0.29	0.22	0.31	**0.63**	**0.70**	26.36	**26.91**	26.69	26.14	**28.57**
Caterpillar	0.18	0.01	0.29	0.23	0.24	**0.30**	**0.36**	25.21	**26.04**	25.12	26.16	**27.81**
Courthouse	0.08	0.11	0.17	0.08	0.09	**0.24**	**0.28**	23.55	25.43	**25.63**	25.06	**27.23**
Ignatius	0.02	0.22	0.83	0.72	0.73	**0.85**	**0.89**	**23.27**	22.69	22.73	**23.78**	**23.67**
Meetingroom	0.08	0.19	0.24	0.04	0.05	**0.27**	**0.32**	25.38	**28.13**	28.05	27.44	**30.70**
Truck	0.35	0.19	**0.45**	0.33	0.37	0.44	**0.48**	23.71	23.89	**23.95**	22.99	**25.43**
Mean	0.15	0.21	0.38	0.27	0.30	**0.45**	**0.50**	24.58	**25.51**	25.36	25.26	**27.24**

Table 2. **Quantitative results on Tanks and Temples dataset [15].** Neuralangelo achieves the best surface reconstruction quality and performs best on average in terms of image synthesis. **Best result**. **Second best result.** Best viewed in color.



(a) Input | w/o $\mathcal{L}_{\text{curv}}$ | w/ $\mathcal{L}_{\text{curv}}$

(b) Input | w/o topology warmup | w/ topology warmup

Figure 7. **Ablation results.** (a) Surface smoothness improves with curvature regularization $\mathcal{L}_{\text{curv}}$. (c) Concave shapes are better formed with topology warmup.

4.4. Ablations

Curvature regularization. We ablate the necessity of curvature regularization in Neuralangelo and compare the results in Fig. 7(a). Intuitively, $\mathcal{L}_{\text{curv}}$ acts as a smoothness prior by minimizing surface curvatures. Without $\mathcal{L}_{\text{curv}}$, we find that the surfaces tend to have undesirable sharp transitions. By using $\mathcal{L}_{\text{curv}}$, the surface noises are removed.

Topology warmup. We follow prior work and initialize the SDF approximately as a sphere [42]. With an initial spherical shape, using $\mathcal{L}_{\text{curv}}$ also makes concave shapes difficult to form because $\mathcal{L}_{\text{curv}}$ preserves topology by preventing singularities in curvature. Thus, instead of applying $\mathcal{L}_{\text{curv}}$ from the beginning of the optimization process, we use a short warmup period that linearly increases the curvature loss strength. We find this strategy particularly helpful for concave regions, as shown in Fig. 7(b).

5. Conclusion

We introduce Neuralangelo, an approach for photogrammetric neural surface reconstruction. The findings of Neuralangelo are simple yet effective: using numerical gradients for higher-order derivatives and a coarse-to-fine optimization strategy. Neuralangelo unlocks the representation power of multi-resolution hash encoding for neural surface reconstruction modeled as SDF. We show that Neuralangelo effectively recovers dense scene structures of both object-centric captures and large-scale indoor/outdoor scenes with extremely high fidelity, enabling detailed large-scale scene reconstruction from RGB videos. Our method currently samples pixels from images randomly without tracking their statistics and errors. Therefore, we use long training iterations to reduce the stochastics and ensure sufficient sampling of details. It is our future work to explore a more efficient sampling strategy to accelerate the training process.

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