Enhancing Surface Neural Implicits with Curvature-Guided Sampling and Uncertainty-Augmented Representations

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Abstract

We present a method that directly digests depth images for the task of high-fidelity 3D reconstruction.

- It introduces a novel local geometry feature computation method such that a simple sampling strategy can be adapted to generate highly effective training data.
- It enables a sampling strategy that can be easily incorporated into diverse popular methods, allowing their training process to be more stable and efficient.
- our method outperforms a range of both classical and learning-based baselines and demonstrates state-of-the-art results in both synthetic and real-world datasets.

One initialized voxel $\mathbf{v}_j$ by integrating depth images stores the following components:

- An approximation ψ_j of its distance $d_{\mathcal{S}}(\mathbf{v}_j)$ to the closest point on the object surface $\mathcal{S}$,
- A vector $\mathbf{g}_j$ approximately parallel to the gradient $\nabla d_{\mathcal{S}}(\mathbf{v}_j)$,
- A differential geometry curvature H_j which computed from depth,
- A scalar uncertainty w_j.

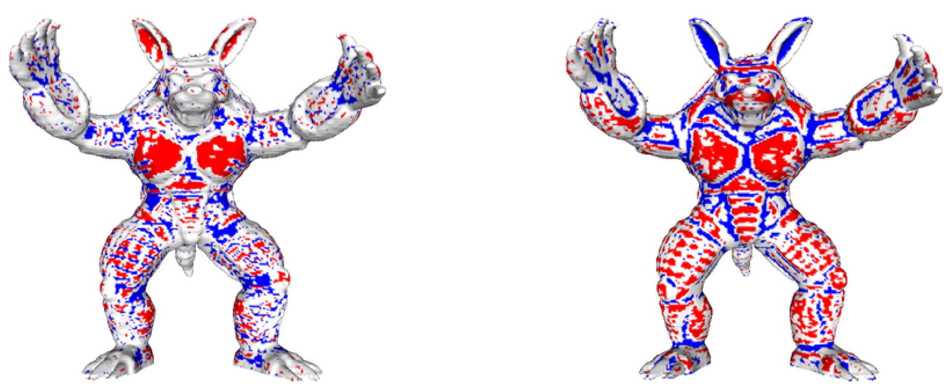
Direct Curvature From Depth

A depth image D can be viewed as a Monge patch of a surface, the Monge patch $\mathcal{M} : \Omega \to \mathbb{R}^3$ is defined as $\mathcal{M}(m,n) = (m, n, D(m,n))$. The two types of curvatures can be computed by

$$K(m,n) = \frac{D_{mm}D_{nn} - D_{mn}^2}{(1 + D_m + D_n)^2}\,, \tag{1}$$

$$H(m,n) = \frac{(1+D_m^2)D_{nn} - 2D_mD_nD_{mn} + (1+D_n^2)D_{mm}}{2(1+D_m^2+D_n^2)^{3/2}}\,, \tag{2}$$

where $D_m = \frac{\partial}{\partial m}D(m,n)$ is the partial derivative of depth w.r.t. x-axis. Similarly $D_n = \frac{\partial}{\partial n}D(m,n)$, $D_{mn} = \frac{\partial^2}{\partial m \partial n}D(m,n)$ and other second order derivatives.



K $\qquad$ H

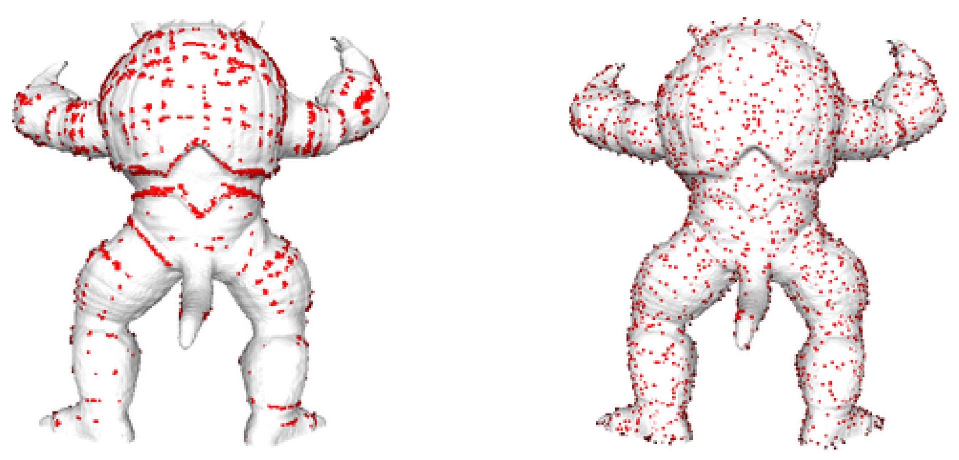
- Positive Gaussian curvature ($K > 0$) indicates that the surface is locally like a dome, and negative Gaussian curvature ($K < 0$) indicates that the surface is locally saddle-shaped.
- A positive mean curvature ($H > 0$) signifies a convex surface, and a negative mean curvature ($H < 0$) indicates a concave surface.

Curvature-guided sampling

the point cloud contained in the voxel grid can simply be extracted in one step (without any mesh extraction) by

$$\mathbf{x}_i = \mathbf{v}_i - \hat{\mathbf{g}}_i^v \psi_i^v, \quad \text{where} \quad \hat{\mathbf{g}}_i^v = \frac{\mathbf{g}_i^v}{\|\mathbf{g}_i^v\|}. \tag{3}$$

To avoid this uneven sampling problem, we divide sampled points into low, median, and high curvature regions based on the mean curvature H which we computed using depth and integrated into the voxel grid.

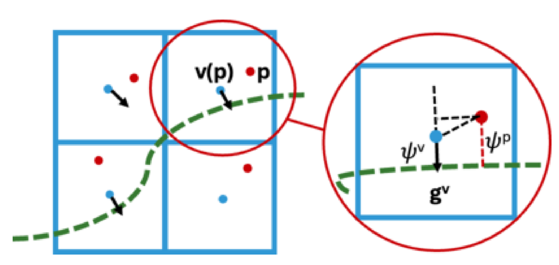


gathering effects $\qquad$ uniform sampling

Off-surface Sampling

To deal with a sparse initialized voxel grid. We sample point $\mathbf{p}$ random in space and get its SDF value ψ^p without rendering a mesh. Using our framework, a randomly sampled point $\mathbf{p}$ its SDF ψ^p this can be computed simply by

$$\psi^p = \psi^v + \langle \hat{\mathbf{g}}^v, \mathbf{p} - \mathbf{v}(\mathbf{p}) \rangle\,, \tag{4}$$



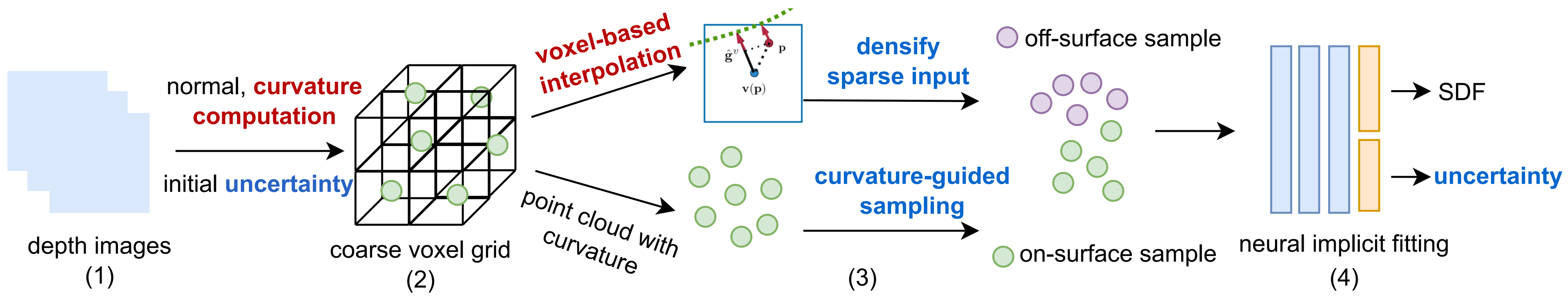


Figure: The summary of our pipeline. The **red** and **blue** correspond to proposed theoretical and architectural contributions. After a customized coarse voxel initialization with uncertainty w^v, curvature H, and normal $\hat{\mathbf{g}}^v$, we use curvature-guided sample on the extracted point cloud and using voxel-based sampling to generate more training points in the space.

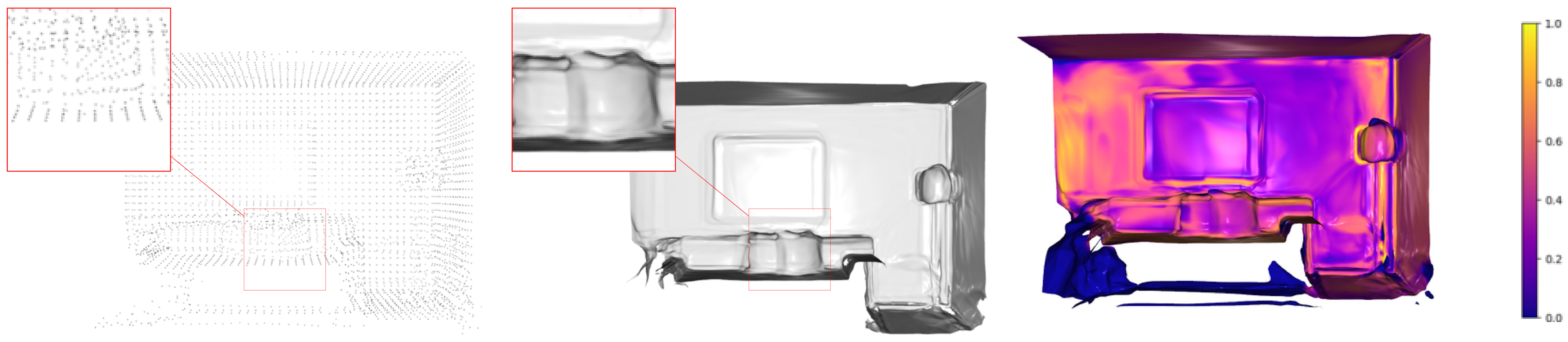


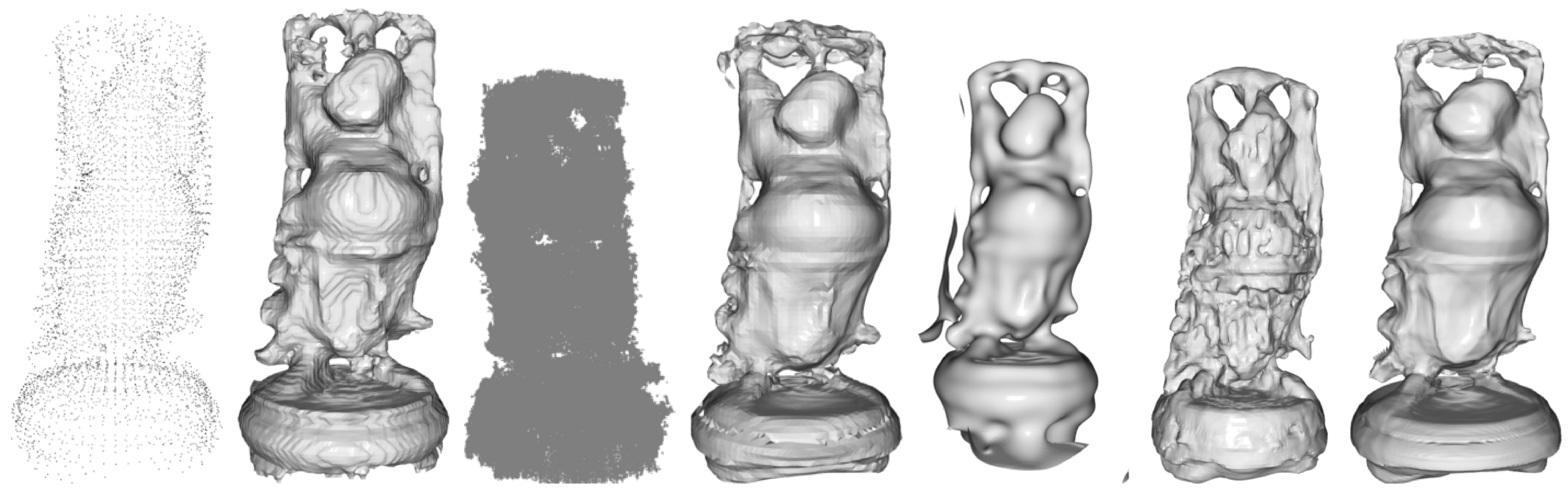
Figure: Our Reconstruction of a room (middle) with sparse input contains only $6k$ points (left) and the estimated uncertainty (right).

Total loss

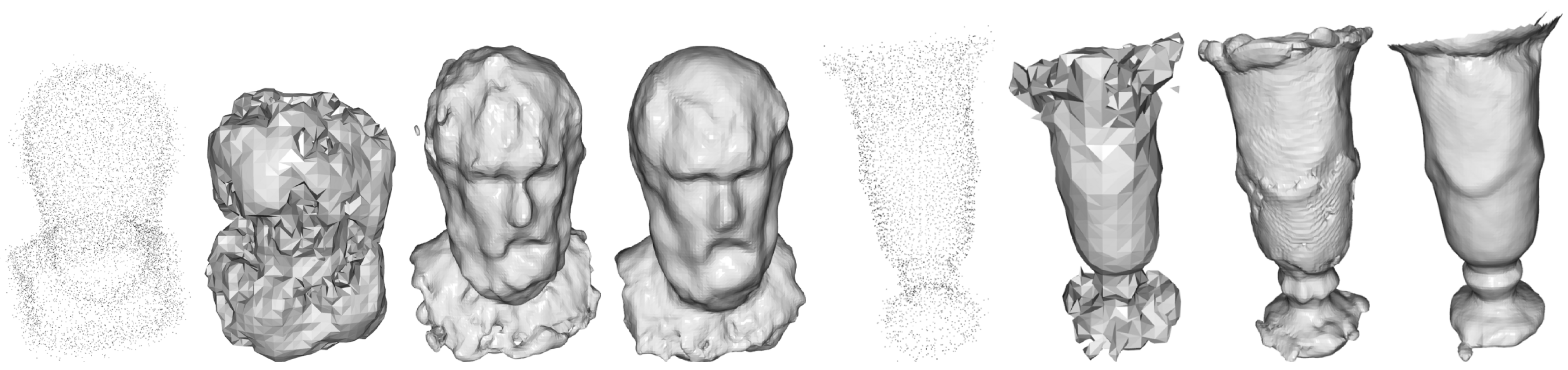
$$l(\theta, \theta_r) = \frac{1}{|\Gamma^+|}\int_{\Gamma^+} \left(|\psi - \psi^p| + (1 - \langle \frac{\nabla_\psi f(\mathbf{p},\theta)}{\nabla_\psi f(\mathbf{p},\theta)}, \hat{\mathbf{g}}^p \rangle)\right) d\Gamma + \frac{1}{|\Gamma|}\int_\Gamma |\nabla_\psi f(\mathbf{p},\theta)^2 - 1| d\Gamma\,. \tag{5}$$

where Γ^+ indicates the area with the sampled uncertainty $w^p > 0$ and θ is the network parameter.

Comparison Results



Real world Results



Project & Contact

Scan me!

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