International Research Journal of Multidisciplinary Sciences ISSN:3107-930X(ONLINE)
VOL-1 ISSUE-8 August 2025 page:24-28

Integrating Geometric Priors in a Modular Deep Learning Framework for Sparse Point Cloud Reconstruction

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Abstract

Reconstructing accurate and watertight 3D meshes from sparse point clouds is a fundamental challenge in computer vision and robotics, with critical applications in augmented reality, autonomous navigation, and cultural heritage preservation. Deep learning methods have shown promise but often produce overly smooth or geometrically inconsistent results when trained on sparse, noisy data. This paper introduces a novel modular deep learning framework that explicitly integrates strong geometric priors to address this limitation. Our architecture consists of three dedicated modules: a Feature Extraction Module that encodes sparse inputs, a Geometric Prior Module that incorporates constraints for surface smoothness and curvature consistency, and a Mesh Reconstruction Module that leverages a differentiable Poisson surface reconstruction layer to generate the final watertight mesh. We evaluate our framework on the ShapeNet and ABC datasets under extreme sparsity conditions (98% point reduction). Quantitative results demonstrate a 15% improvement in Chamfer Distance and a 12% improvement in F-Score@1% over state-of-the-art methods like PointeNet and ONet. Qualitatively, our reconstructions preserve sharp features and fine details that other methods fail to capture. This work establishes that the explicit, modular integration of geometric priors is essential for robust and high-fidelity 3D reconstruction from sparse inputs.

Keywords: 3D Reconstruction, Point Cloud, Deep Learning, Geometric Priors, Modular Architecture, Differentiable Rendering, Poisson Reconstruction.

1. Introduction

The acquisition of 3D data via LiDAR, RGB-D sensors, or photogrammetry often results in point clouds that are incomplete, noisy, and sparse. Converting these sparse observations into a continuous, watertight surface representation—a process known as 3D reconstruction—is an ill-posed problem. While deep learning has revolutionized this field, data-driven approaches trained end-to-end can struggle to learn fundamental geometric properties from limited data, leading to solutions that are physically implausible. This paper posits that the integration of explicit, domain-specific geometric knowledge is necessary to guide the learning process and ensure robust results. We present a modular framework that disentangles the learning of data-driven features from the enforcement of geometric constraints. This design not only improves performance but also enhances the interpretability and controllability of the reconstruction process. The core research questions we address are: (RQ1) How can geometric priors for surface smoothness and structure be effectively integrated into a deep learning pipeline? (RQ2) Does a modular approach outperform monolithic end-to-end architectures in sparse reconstruction tasks? (RQ3) Can this framework generalize to real-world sparse data from different sensors?

2. Related Work

2.1 Deep Learning on Point Clouds: Pioneering work by Qi et al. [1] with PointNet introduced a architecture for directly processing unordered point sets. Subsequent works like PointNet++ [2] and DGCNN [3] improved upon this by capturing local features and hierarchical structures.

2.2 Implicit Surface Reconstruction: A significant shift occurred with the adoption of implicit functions. Occupancy Networks (ONet) [4] and DeepSDF [5] learn to classify 3D space as inside or outside an object, enabling high-quality mesh extraction. However, these methods can struggle with **sparsity and often output overly smooth surfaces.**

2.3 Explicit Priors in 3D Learning: The need for geometric constraints is well-recognized. Previous works have incorporated physical constraints [6], symmetry [7], and learned regularizers [8]. However, these are often baked into a single loss function within a monolithic network. Our work differs by architecturally separating the prior into a dedicated, reusable module.

2.4 Differentiable Surface Reconstruction: Key to our approach is the use of a differentiable renderer. Previous efforts have made rasterization [9] and Poisson reconstruction [10] differentiable, allowing gradients to flow through the mesh formation process itself. We build upon these ideas to integrate a differentiable Poisson solver within our modular pipeline.

3. Methodology: The Proposed Modular Framework

Our framework comprises three core modules that operate sequentially while allowing for gradient flow during training.

3.1 Feature Extraction Module:

This module takes a sparse point cloud `P ∈ R^(N×3)` and associated normals (estimated or learned) as input. We use a modified PointNet++ architecture with set abstraction layers to extract a multi-scale global feature vector `f_global` and a set of local features `F_local`. This captures both the overall shape context and fine-grained local geometry.

3.2 Geometric Prior Module (GPM):

This is the novel component of our architecture. The GPM operates on the local features `F_local` and imposes two key priors:

Smoothness Prior: A graph convolutional network (GCN) is applied over a k-NN graph constructed from the input points. This encourages similar features for points lying on locally smooth regions of the surface.

Curvature Consistency Prior: A secondary network branch predicts a per-point curvature estimate. A regularization loss `L_curv` minimizes the variance of curvature values within local neighborhoods, discouraging the network from creating geometrically irregular "spikes" or "dips" in the reconstructed surface.

The output is a refined set of features `F_refined` that are geometrically consistent.

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3.3 Differentiable Mesh Reconstruction Module:

The refined features `F_refined` are used to predict a dense, oriented point cloud `D ∈ R^(M×6)` (positions + normals), where `M >> N`. This dense cloud is then passed through a Differentiable Poisson Surface Reconstruction (DPSR) layer [10]. The DPSR layer solves a linear system to produce a watertight mesh `M` and, crucially, allows gradients to be backpropagated from the final mesh to the predicted dense points, enabling end-toend training.

3.4 Loss Functions:

The total loss is a combination:

`L_total = L_chamfer(D, D_gt) + λ1 L_curv + λ2 L_occupancy(M, M_gt)`

where `L_chamfer` ensures the predicted dense cloud matches the ground truth, `L_curv` is the curvature consistency loss, and `L_occupancy` is a loss between the reconstructed and ground truth meshes.

4. Experimental Setup

4.1 Datasets: We use ShapeNet [11] for categorical evaluation and the ABC dataset [12] of CAD models for evaluating geometric precision. We simulate sparsity by randomly sub-sampling point clouds to 1-2% of their original density.

4.2 Baselines: We compare against:

Traditional: Poisson Surface Reconstruction (PSR) [13].

Learning-Based: PointeNet [14], ONet [4], and DISN [15].

4.3 Metrics: Chamfer Distance (CD), Earth Mover's Distance (EMD), F-Score@1%, and Normal Consistency (NC).

5. Results and Analysis

Table 1: Quantitative Results on ShapeNet (Sparse Setting)

Method	CD (↓)	F-Score@1% (↑)	NC (↑)
PSR	3.45	0.412	0.845

| PointeNet | 2.01 | 0.503 | 0.881 |

| ONet | 1.87 | 0.528 | 0.892 |

| Ours | 1.59 | 0.591 | 0.918 |

Discussion: Our method consistently outperforms all baselines across all metrics. The qualitative results are particularly striking: while baseline methods produce smoothed-out or fragmented surfaces on thin structures (e.g., chair legs, airplane wings), our reconstructions preserve these sharp features due to the explicit curvature constraints in the GPM.

6. Ablation Study and Discussion

We conduct an ablation study to validate our design choices:

w/o GPM: Removing the Geometric Prior Module leads to a 22% increase in CD, confirming its necessity.

w/o Curvature Loss: Removing `L_curv` results in noticeably noisier surfaces, especially in regions of high curvature.

w/o Differentiable PSR: Replacing the DPSR layer with a non-differentiable step creates a training-inference mismatch and degrades performance.

The main limitation is the computational cost of the DPSR layer during training, which can be memory-intensive for very large scenes.

7. Conclusion and Future Work

We presented a novel modular framework for sparse point cloud reconstruction that explicitly enforces geometric priors within a deep learning pipeline. The modular design offers a principled way to integrate domain knowledge, leading to state-of-the-art performance on sparse data. Future work will focus on: 1) Incorporating semantic priors for class-specific structure, 2) Extending the framework to handle dynamic scenes, and 3) Optimizing the DPSR layer for faster training.

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