

BPA-Assisted Screened Poisson Reconstruction of Sparse Point Clouds: Disentangling Support-Conditioned Resampling, Densification, and Normal Processing

Huiting Chen

Chinese Academy of Sciences

Bo Hu

University of Illinois Urbana-Champaign

Shui Liu

Chinese Academy of Sciences

Jian He

hej@sari.ac.cn

Chinese Academy of Sciences

Research Article

Keywords: point cloud, surface reconstruction, screened Poisson, ball pivoting, normal orientation, evaluation protocol

Posted Date: October 26th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11055458/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

BPA-Assisted Screened Poisson Reconstruction of Sparse Point Clouds: Disentangling Support- Conditioned Resampling, Densification, and Normal Processing

Authors: Huiting Chen ^{a,#}, Bo Hu ^{b,#}, Shui Liu^a, Jian He ^{a,*}

^a Shanghai Advanced Research Institute, Chinese Academy of Sciences, Shanghai 201204, China

^b Department of Statistics, University of Illinois Urbana-Champaign, Champaign, IL 61820, USA

[#]These authors contributed equally to this work

^{*}Corresponding authors: hej@sari.ac.cn(J. He)

Abstract. Screened Poisson reconstruction (SPR) can degrade sharply on sparse point clouds. A common engineering remedy is to construct partial geometric support by multi-scale ball pivoting (BPA), resample it, re-estimate normals, and only then apply SPR. The source of the resulting improvement is rarely isolated. We decompose the remedy into three experimental factors (BPA-support-conditioned redistribution, densification of the fixed support, and the normal-orientation procedure) and test them on three benchmarks with 10 matched seeds per condition.

On a fixed BPA support, raising the resampling budget from N to 10^4 points is the only intervention that helped in every case we tested: normalized Chamfer error improved by 1.5–15.7× in all nine object–density cells, under both orientation procedures, with paired bootstrap CIs excluding zero throughout. Resampling the support also tames orientation sensitivity: switching between a camera-location heuristic and tangent-plane propagation changes error by up to 21× on raw inputs, shrinking to 5.7× and 2.6× after same-count and dense resampling. There is a limit, however. An oracle-normal control on dragon, the one benchmark whose reference

carries normals, shows that direct SPR with exact normals surpasses the complete pipeline by 1.9–4.3×. Normal quality remains an independent accuracy limitation even after support-conditioned densification.

Separately, Open3D’s native multi-radius BPA invocation collapses to 8 triangles (our support: 622), yet vertex-set metrics score the two identically. Under 4:1 non-uniform sampling the advantage over direct SPR reverses on one of three models, bounding the regime in which the preprocessing helps. We release all scripts, seeds, and per-seed results.

Keywords. point cloud, surface reconstruction, screened Poisson, ball pivoting, normal orientation, evaluation protocol

Introduction

Screened Poisson reconstruction (SPR) [2] is the default implicit reconstructor for oriented point clouds, but it degrades rapidly when the input is *sparse*. With 10^3 points on a unit-scale object, an oriented global solve invents geometry where none is constrained and smooths away what is real; in our experiments, error grows by an order of magnitude between 2×10^4 and 10^3 input points (Section 7). A standard remedy in the applied literature is to precondition the cloud: run ball pivoting (BPA) at several radii to grow partial patches, resample the patches, re-estimate and re-orient normals, and hand the result to SPR. The remedy is plausible and it works. But no controlled comparison isolates *which ingredient does the work*. The question is not academic. If the gain comes from the geometric support, the pipeline should be tuned around BPA. If from added points, a cheaper resampling primitive may suffice. If from normal stabilization, the evaluation protocol that produced the evidence must control for normals - and most comparisons in this space do not.

This paper answers that question for a representative, fully disclosed pipeline: multi-scale BPA with radii $\{0.3, 0.6, 1.2\} \cdot d$ (d is the mean nearest-neighbor distance of the input), uniform resampling of the merged patches, PCA normal estimation with tangent-plane orientation propagation, and SPR with density trimming and hole filling. We specify three competing causal hypotheses before running any of the causal experiments: (A) orientation-dominant, (B) support-conditioned orientation, and (C) support/density-dominant. They are tested with a factorial experiment on a fixed support, an oracle-normal control, and a normal-error mediator analysis, all with 10 matched seeds.

The results only partially fit any of the three hypotheses, and the mismatches pointed to a different explanation. The factorial shows that on a fixed support, resampling from N to 10^4 points is the only universally positive intervention (1.5–15.7× across all nine object–density cells, both orientation procedures, all paired 95% bootstrap CIs excluding zero). The same factorial shows that the choice of

orientation procedure, severe on raw inputs (up to 21 $\times$), is reduced but not removed by support resampling (5.7 $\times$ at same-count, 2.6 $\times$ at dense resampling), though the sign of the residual difference depends on the object. The oracle control shows the opposite limit: given exact normals, plain SPR on the raw cloud beats the full pipeline by 1.9–4.3 $\times$. No support mechanism removes the accuracy ceiling set by normal quality. We also find that one implementation choice is load-bearing: Open3D’s native multi-radius BPA call collapses to 8 triangles on our inputs, versus 622 for independent-per-radius pivoting with concatenation, while returning the identical vertex array. Vertex-set metrics, still common in this literature, score the two identically. Finally, a 4:1 non-uniform sampling stress test reverses the pipeline’s advantage over direct SPR on one of three models, which bounds the regime in which the preprocessing helps at all.

The contributions are:

- **A controlled decomposition** of BPA-assisted SPR into same-count redistribution from BPA-derived support, densification of the fixed support, and normal-processing effects, using a fixed-support factorial (7 conditions $\times$ 9 object–density cells $\times$ 10 matched seeds) with hypotheses specified a priori.
- **Evidence for a dual mechanism:** within the tested factorial, increasing the resampling budget on a fixed BPA-derived support is the only intervention that improves nCD in every object–density cell under both tested normal procedures (1.5–15.7 $\times$, all paired CIs excluding zero), and dense support resampling reduces worst-case orientation-procedure sensitivity from 21 $\times$ to 2.6 $\times$. Oracle normals, meanwhile, establish normal quality as an independent ceiling.
- **An implementation and evaluation audit:** the native multi-radius BPA collapse (8 vs 622 triangles, identical vertex array), which vertex-set metrics cannot see; a mesh-reference analysis on dragon showing that symmetric squared-mean metrics are dominated by uncovered area at low sampling; and a mediator analysis (nearest-neighbor coefficient of variation) that rules out first-order neighborhood uniformity as the mechanism of the densification gain.
- **A delimited regime:** the pipeline improves on direct SPR by 1.4–4.9 $\times$ under moderate non-uniform sampling on two of three models but reverses (0.43 $\times$) on the third at $N = 5000$, and it loses to direct BPA on near-complete inputs. We report these negative results alongside the positive ones.

Section 2 positions the study in the literature. Section 3 describes the pipeline and the hypotheses; Section 4, the evaluation protocol; Section 5, the causal

experiments; Section 6, the controls; Section 7 returns to the end-to-end comparison.

Related Work

Implicit reconstruction and its inputs. Poisson surface reconstruction formulates recovery as an indicator-function solve [1]; the screened variant [2] adds point constraints and is the variant implemented in Open3D [3], which we use throughout. The solver requires oriented points. Classical orientation pipelines estimate PCA normals and propagate them over a minimum spanning tree [4], as Open3D does, or apply simpler heuristics. Our study is agnostic to the solver: we hold SPR fixed and vary the preprocessing.

Ball pivoting and multi-scale triangulation. BPA [5] grows a triangulation from a seed edge whenever a rolling ball of given radius touches a third point; it never invents vertices. A single radius is hole-prone under non-uniform sampling, and running several radii is the folklore fix. We show that *how* the multi-radius variant is invoked matters. The native list invocation in Open3D 0.19 collapses on sparse inputs, so we pivot each radius independently and merge by vertex-offset concatenation.

Preprocessing before implicit reconstruction. Upsampling, MLS smoothing, and normal refinement before implicit solves are standard practice in scanning pipelines [6]. None of these applied reports isolates cause: end-to-end gains conflate support construction, sample count, sampling distribution, and normal processing. Our factorial separates these factors. The closest methodological template is the ablation practice of learning-based reconstruction [7], which we import to a classical pipeline where it is rarely applied.

Normal-free reconstruction. PGR [8] reconstructs from unoriented clouds by parametrizing the Gauss formula and is the strongest normal-free baseline; its released outputs serve here as contextual reference only, since our controlled inputs differ from its benchmark configuration. Fast winding numbers [9] support orientation-free queries but presuppose closed proxies.

Evaluation of reconstructed surfaces. Chamfer and Hausdorff metrics over point samples are standard, but conventions differ (squared vs. linear, one- vs. two-sided, vertices vs. surface samples), and finite reference sets introduce bias that is rarely quantified [10]. We adopt surface-sampled, normalized, bidirectional metrics with stated conventions, and we quantify their limits rather than assume them. A mesh-reference audit on dragon (Section 4) shows that symmetric squared means are dominated by uncovered area once inputs are sparse, and that point-reference benchmarks cannot resolve the sub-10% differences often used to declare winners.

Pipeline and Causal Factors

The pipeline

Given an input cloud $P \subset \mathbb{R}^3$ with N points ($5 \times 10^2 \leq N \leq 4 \times 10^4$), the pipeline produces a reconstructed surface mesh in three stages (Fig. 1):

- **Stage 1 (independent-per-radius BPA support).** PCA normals (radius 0.05, 15 neighbors) are estimated on the input and oriented by an outward heuristic (toward the bounding-box center + z), merely to satisfy BPA’s input requirement (Section 3.2). BPA then runs independently at radii $\{0.3, 0.6, 1.2\} \cdot d_{\text{in}}$, where d_{in} is the mean nearest-neighbor distance of the input (400-point KD-tree subsample), and the partial meshes are concatenated by vertex offset. This construction is not cosmetic: Open3D’s native multi-radius invocation collapses on our inputs (Section 6.1).
- **Stage 2 (support resampling and orientation).** The merged patches are resampled by area-weighted triangle sampling (our implementation, seeded; Open3D’s sampler is unseeded in this build) with budget $n_s = \max(10^4, N)$. Normals are re-estimated by local PCA (radius 0.01, 30 neighbors) and oriented consistently by tangent-plane propagation ($k = 15$).
- **Stage 3 (SPR and cleanup).** Screened Poisson (depth 10, scale 1.0, linear fit; our fixed settings, not solver defaults) with 2% density trimming, hole filling (≤ 100 edges), and removal of non-finite vertices. Non-finite vertices occurred in 3 of 24 benchmark meshes we inspected (26/2/10 vertices). We treat sanitization as mandatory engineering.

Pre-BPA normals

BPA consumes normals in its candidate-face compatibility test (a candidate triangle is rejected unless its normal agrees with all three vertex normals), so normal signs can influence triangulation topology, not merely triangle winding. We therefore do *not* claim orientation-insensitivity for Stage 1. Section 6.2 ablates the pre-BPA orientation procedure and finds the final-pipeline effect small ($\leq 1.32\times$, sign inconsistent across models). We report this as an empirical observation in our operating regime, not as a theoretical property.

d_{in} versus d_s

All radii in Stage 1 anchor to the input spacing d_{in} . After resampling, the support’s spacing is different, so any d -scaled parameter in Stage 2 must anchor to the *resampled* spacing d_s , not d_{in} . One caveat applies throughout: reconstruction runs in native benchmark coordinates, so the normal neighborhoods 0.05 (pre-BPA) and 0.01 (post-resampling) are scale-dependent fixed hyperparameters. The

benchmark models span a narrow scale range (bounding-box diagonals 0.26–1.9), and Section 6.4 measures sensitivity to scaling them. We state the caveat rather than silently assume scale invariance.

Causal hypotheses specified a priori

We compare three hypotheses on why BPA preconditioning helps SPR:

- **A (orientation-dominant):** consistent orientation propagation is the decisive enabler; with tangent-plane propagation, direct SPR approaches the full pipeline.
- **B (support-conditioned orientation):** tangent propagation helps, but only the BPA support makes it reliable. Support and orientation interact.
- **C (support/density-dominant):** geometric support and densification explain the gain regardless of normal processing.

Section 5 adjudicates these with a fixed-support factorial, oracle normals, and mediator statistics. We state upfront that all three fail in some regime and are replaced by the account developed in Section 5.6.

Experimental Design and Evaluation Protocol

Benchmarks. Bunny (20,000-point GT), dragon (4.4×10^5 -vertex reference mesh), and horse (9,697-point GT), from the PGR release distribution. Controlled inputs are uniform random subsamples of the ground truth at prescribed densities with 10 matched seeds (generated from fixed seeds 1000–1009); every condition sees identical inputs.

Metrics. All coordinates are normalized by the ground-truth bounding-box diagonal before metric computation. The reconstruction mesh is surface-sampled by seeded, area-weighted triangle sampling (5×10^4 points, after sanitization); the reference is capped at 2×10^5 points. We report bidirectional squared Chamfer distance (nCD), bidirectional 95th-percentile Hausdorff distance (HD95), and maximum Hausdorff distance (HDmax, supplementary). Paired seed-level effects are summarized as mean log-ratios with 95% bootstrap confidence intervals (percentile method, 10,000 resamples of the 10 matched seed-level log-ratios, fixed RNG seed 42). We state these conventions because mixed squared/linear and vertex/surface choices are a documented source of irreproducibility in this literature.

Why vertex-based evaluation is excluded. BPA’s vertices are input points, so vertex-based Chamfer collapses toward zero as inputs densify, independent of surface quality. Section 6.1 gives a clear demonstration: two supports producing 8 and 622 triangles receive *identical* vertex-based scores.

Reference limits. Bunny/horse references are finite point sets; dragon is a mesh. For dragon we additionally compute the exact nearest-triangle distance for each sampled query point in both directions (reconstruction vertices queried against the reference mesh; 2×10^5 area-weighted reference samples queried against the reconstruction) and show that symmetric squared means are dominated by uncovered area at low N (Section 5.4). We therefore (i) conservatively treat sub-10% differences on point-reference-only benchmarks as unresolved, and (ii) report paired seed-level log-ratios with bootstrap 95% CIs instead of comparing averaged cells.

Conditions. Throughout, “camera” denotes PCA normals plus outward heuristic; “tangent” denotes PCA normals plus tangent-plane propagation ($k = 15$). “Support” denotes the Stage-1 concatenation; “rsN” and “rs10k” denote resampling the support to N or 10^4 points. Oracle normals (dragon only, the only reference with normals) are ground-truth vertex normals transferred to input points and fed directly to SPR without re-estimation.

Causal Decomposition

Raw-input orientation sensitivity

Table tab2 (columns raw_cam/raw_tan) shows the two orientation procedures applied directly to the raw sparse inputs. The effect is large and object-dependent. On horse, camera orientation is 17.7–21.0× worse than tangent propagation (nCD 5.65×10^{-3} vs 3.23×10^{-4} at $N=1000$). On dragon the ordering reverses: tangent is 1.4–3.4× worse. On bunny the two are indistinguishable ($\leq 1.02\times$). Hypothesis A already fails in its strong form, because tangent propagation does not uniformly help direct SPR.

Fixed-support factorial

Table tab2 holds the Stage-1 support fixed per (object, N , seed) and varies resampling budget {rsN, rs10k} × orientation {camera, tangent}; Fig. 2 plots the paired effects. The densification main effect is the only universally positive result in the study. It improves nCD in all 18 (cell × orientation) comparisons by 1.5–15.7×, with paired seed-level log-ratios whose 95% bootstrap CIs exclude zero everywhere. The effect is largest at the sparse end (15.7×, horse $N=1000$, camera) and decays with density (1.5×, dragon $N=5000$), consistent with a sampling-density bottleneck that shrinks as inputs densify.

Interaction: orientation sensitivity is support-conditioned

The orientation main effect at rs10k is bounded by 2.6× in absolute value across all cells; at rsN it reaches 5.7× (horse, $N=2500$); on raw inputs it reaches 21× (same

object); Fig. 2b plots all cells. The interaction is heterogeneous in sign. On bunny, dense resampling slightly *favors* camera orientation (1.1–1.8×). What survives across cells is narrower: **dense support resampling suppresses the worst-case sensitivity to the orientation procedure from 21× (raw) to 5.7× (same-count support) to 2.6× (dense support)**. This is the interaction evidence for hypothesis B - and the sign heterogeneity is why B fails in its original “tangent becomes decisive” form.

Oracle normals: the ceiling

Feeding exact reference normals to direct SPR on dragon (no re-estimation) yields nCD 1.80×10^{-4} / 6.40×10^{-5} / 3.00×10^{-5} at $N=1000/2500/5000$. The full pipeline gives 3.40×10^{-4} / 1.82×10^{-4} / 1.29×10^{-4} ; oracle normals surpass it by 1.9–4.3×. This fails hypothesis C on dragon: geometric support is not intrinsically necessary when normal quality is high enough. It also means that on dragon, normal quality remains an independent bottleneck. Sufficiently accurate normals eliminate and reverse the pipeline’s advantage over direct SPR, so residual headroom on this benchmark should be pursued in normal estimation rather than in more elaborate densification. The oracle is a diagnostic (exact normals are unavailable in the target applications) and exists only for dragon; we do not extrapolate the ceiling claim to bunny or horse.

A protocol note from the dragon mesh reference. Nearest-triangle symmetric squared means (sample-based in the reference→reconstruction direction) at $N=1000$ are ≈ 0.1 for *all* methods, an order of magnitude larger than any point-reference nCD, because uncovered reference area dominates the symmetric mean once inputs are sparse. Method ordering under this metric is unstable across N . We therefore restrict point-reference claims to the $\geq 10\%$ effects carried by paired seed comparisons. Squared symmetric means over partial reconstructions are unfit for fine-grained ranking; here we have quantified that limit rather than assumed it.

Mediator analysis: what densification does *not* do

If densification worked by regularizing local neighborhoods, the nearest-neighbor coefficient of variation (NN-CV) of the resampled support should improve with budget. It does not. NN-CV is 0.40–0.56 on raw inputs, *rises* to 0.87–1.06 at rsN, and only partially recovers (0.61–0.90) at rs10k; the rise reflects duplicate-area coverage by the three radius passes. The NN-CV result rules out first-order spacing uniformity as a sufficient explanation of the gain. Geometric coverage of holes and changes in the conditioning of the downstream implicit solve remain plausible but untested mediators. We deliberately do not name one.

Adjudication: a dual-mechanism account

A fails on dragon and bunny (Section 5.1); C fails under oracle normals (Section 5.4); B fails in sign heterogeneity (Section 5.3). What the experiments leave standing is two separable limitations:

On sparse inputs, BPA-assisted SPR is governed by two separable limitations. Geometry-conditioned densification (resampling a conservative BPA support at a large, uniform budget) provides the most consistent practical accuracy gain (1.5–15.7×) and tames the otherwise severe object dependence of heuristic orientation ($21\times \rightarrow 2.6\times$). Normal quality sets an independent ceiling: with oracle normals, plain SPR surpasses the entire pipeline.

In practice the pipeline trades peak accuracy for a specific robustness: its result does not depend on which normal-orientation procedure is used, and it requires no externally supplied normals.

Architecture and Robustness Controls

Native multi-radius BPA collapses; concatenation is load-bearing

Invoking Open3D 0.19’s BPA with the radius *list* $\{0.3, 0.6, 1.2\} \cdot d$ on our sparse inputs produces 8 triangles (horse, $N=1000$; 11 of 1000 input vertices touched; Fig. 4). Invoking the same radii independently and concatenating produces 622 triangles (739 vertices touched). The two supports return the *identical* vertex array, so a vertex-based Chamfer (common in applied studies) scores them identically, although one is a void and the other a surface. Downstream, the native-collapse route degrades the final pipeline by 7–2529× across our cells (Table tab3). Both effects are specific to this library version and these input densities. Practically, independent-per-radius pivoting with explicit concatenation is necessary under Open3D 0.19 with sparse inputs. Methodologically, vertex-set metrics are not merely biased; here they were blind to a 78× triangle-count collapse.

Pre-BPA orientation

Ablating the pre-BPA orientation procedure (camera vs tangent propagation, $N \in \{1000, 10^4\}$, 5 seeds) changes Stage-1 triangle counts by ~10% and final pipeline nCD by at most 1.32×, with inconsistent sign across models (bunny 0.92–1.13, dragon 0.89–1.11, horse 0.90–1.32). In our operating regime the final result is insensitive to this choice. We do not claim this generalizes.

Non-uniform sampling

Retaining points on one half-plane at $4\times$ the rate of the other ($N \in \{1000, 5000\}$, 5 seeds), the pipeline keeps $1.4\text{--}4.9\times$ lower nCD than direct SPR on bunny and horse at $N=1000$ and parity to $0.95\times$ at $N=5000$. On dragon at $N=5000$ the pattern reverses (ours/spr = 2.33). Outside approximately uniform sampling, the global- d anchoring that Stage 1 depends on stops conferring an advantage. We report this reversal as a bound on the method’s regime.

Parameter sensitivity

At $N = 1000$ (3 seeds, 3 objects), varying the radius triplet $\{(0.2, 0.5, 1.0), (0.3, 0.6, 1.2), (0.5, 1.0, 2.0)\} \cdot d$ changes mean nCD by $0.53\text{--}3.09\times$ relative to the shipped $\{(0.3, 0.6, 1.2)\}$ configuration; scaling the Stage-2 normal radius $\{0.5\times, 1\times, 2\times\}$ changes it by $0.54\text{--}1.60\times$ (Table tab4). The larger-radius triplet is consistently equal or *better* ($0.53\text{--}0.88\times$ on all three objects). We report this observation but retain the shipped configuration for all main results, since re-tuning on the test objects would compromise the fixed-protocol claim. The shipped configuration sits within $1.9\times$ of the best observed combination on every object. The radii are nondimensionalized but not optimized; we report the stable region they define, with no claim of optimality.

Mesh validity

Neither the pipeline nor direct SPR yields watertight meshes after density trimming (0% watertight across all audited cells; Table tab5); trimming removes low-density regions by design and thereby opens the surface. The pipeline’s meshes are $15\text{--}19\times$ larger in faces and carry $3\text{--}30\times$ fewer non-manifold edges than direct SPR’s at the same N , with more boundary edges in absolute terms (a consequence of size and trimming). We therefore withdraw any “watertightness” advantage for the pipeline; the defensible statement is fewer non-manifold structures, comparable closedness (both imperfect), and larger output.

Comparative Regime Map (Supporting Validation)

Table tab1 revisits the original end-to-end comparison under the current protocol, as supporting validation rather than the principal result. Against directly applied SPR the pipeline wins at every tested operating point ($1.5\text{--}57\times$). This end-to-end comparison shows the practical performance gap; causal attribution of the gap follows from the controlled experiments of Section 5, not from this comparison itself. Against directly applied single-radius BPA the outcome is regime-dependent: wins at $N=10^3$ on bunny (-38%) and horse (-56%), loses on dragon ($+61\%$). Near-complete inputs favor BPA: at these densities its piecewise-linear interpolation over the samples is already close to the reference, and densification has nothing left to

add. PGR remains stronger where its released outputs exist (bunny –15%, dragon –55% relative to the pipeline in nCD); those outputs come from a different input configuration and are contextual only.

Runtime. End-to-end pipeline: 0.7–1.9 s for 10^3 – 2×10^4 input points on a laptop CPU (i7-13700H). Direct SPR is $\sim 3\times$ faster and direct BPA faster still. Runtime is an engineering property; we no longer headline it.

Limitations

(i) The final solver is stock SPR; the contribution is the decomposition, not a new formulation. (ii) The pipeline loses to direct BPA on dragon at all densities and near-complete inputs generally; densification pays only when inputs are genuinely sparse. (iii) PGR outperforms the pipeline on its released benchmarks. (iv) Under strong non-uniformity the global- d anchoring can lose to direct SPR (dragon, 4:1, $N=5000$); locally adaptive radii remain future work. (v) Oracle controls exist only where references carry normals (dragon); the ceiling argument is untested on bunny/horse. (vi) Ten seeds resolve the reported effects (all CIs exclude zero) but are not a large-scale statistical study. (vii) The mediator for the densification gain is unidentified: first-order neighborhood uniformity is refuted, and candidates such as hole coverage and solve conditioning are untested. (viii) All quantitative inputs are clean uniform subsamples of references; noisy acquisition is untested, and we accordingly position this work as classical geometry/computing, not as a metrology validation. (ix) The native-BPA collapse is scoped to Open3D 0.19.

Conclusion

The controlled experiments identify two distinct limitations behind the improvement of BPA-assisted SPR on sparse inputs. Support-conditioned densification consistently improves reconstruction within the tested regime, and it suppresses a severe failure mode of raw-input pipelines: orientation instability. Normal quality independently constrains the attainable accuracy: on dragon, oracle normals let plain SPR overtake the full pipeline entirely. Around these findings we documented an implementation trap (the native multi-radius invocation collapse, invisible to vertex-based metrics) and a protocol trap (finite references and uncovered area dominating symmetric means), both with direct evidence. The regime in which the preprocessing helps is now bounded: sparse, approximately uniform inputs. The regime where it fails is stated, not hidden. We release scripts, seeds, per-seed results, and all figures.

Declarations

- **Funding.** The work is supported by the Chinese Academy of Sciences, Shanghai Branch (E46G451401), and the Strategic Priority Research Program of the Chinese Academy of Sciences (XDB1180000).
- **Conflict of interest.** The authors declare no competing interests.
- **Data and code availability.** All reconstruction scripts, evaluation scripts, fixed seeds, per-seed results, and figure sources are released with the submission. Third-party inputs: bunny/dragon/horse from the PGR release [8]; horse-PGR regenerated with the official PGR implementation (CPU, default parameters).
- **Authors' contributions.** [to be completed by the authors]
- **Use of large language models.** During preparation of this work the authors used ChatGPT (OpenAI) to assist with language editing and to organize internal review comments. All experiments, data analysis, figures, and scientific conclusions were produced and verified by the authors, who reviewed the content and take full responsibility for it.

12

Kazhdan M, Bolitho M, Hoppe H: Poisson surface reconstruction. In: Symposium on Geometry Processing, pp 61-70 (2006). <https://doi.org/10.2312/SGP/SGP06/61-70>

Kazhdan M, Hoppe H: Screened Poisson surface reconstruction. ACM Trans Graph 32, 29 (2013). <https://doi.org/10.1145/2461912.2461945>

Zhou Q-Y, Park J, Koltun V: Open3D: A modern library for 3D data processing. arXiv:1801.09847 (2018)

Hoppe H, DeRose T, Duchamp T, McDonald J, Stuetzle W: Surface reconstruction from unorganized points. ACM SIGGRAPH Comput Graph 26, 71-78 (1992). <https://doi.org/10.1145/133994.134011>

Bernardini F, Mittleman J, Rushmeier H, Silva C, Taubin G: The ball-pivoting algorithm for surface reconstruction. IEEE Trans Vis Comput Graph 5, 349-359 (1999). <https://doi.org/10.1109/294912>

Berger M, Tagliasacchi A, Seversky LM, Alliez P, Guennebaud G, Levine JA, Sharf A, Silva CT: A survey of surface reconstruction from point clouds. Comput Graph Forum 33, 163-182 (2014). <https://doi.org/10.1111/cgf.12281>

Huang J, Gojcic Z, Atzmon M, Litany O, Fidler S, Williams F: Neural kernel surface reconstruction. IEEE Trans Pattern Anal Mach Intell 45, 5646-5658 (2023). <https://doi.org/10.1109/TPAMI.2022.3161072>

Lin S, Xiao D, Shi Z, Wang B: Surface reconstruction from point clouds without normals by parametrizing the Gauss formula. ACM Trans Graph 41, 1-19 (2022). <https://doi.org/10.1145/3550504>

Barill G, Dickersson N, De Goes F, Jacobson A: Fast winding numbers for soups and clouds. ACM Trans Graph 37, 109 (2018). <https://doi.org/10.1145/3202664>

Tatarchenko M, Richter S-R, Ranftl R, Li Z, Koltun V, Brox T: What do single-view 3D reconstruction networks learn? In: IEEE/CVF CVPR, pp 5491-5500 (2019). <https://doi.org/10.1109/CVPR.2019.00562>

Lorensen WE, Cline HE: Marching cubes: a high resolution 3D surface construction algorithm. ACM SIGGRAPH Comput Graph 21, 163-169 (1987). <https://doi.org/10.1145/358523.358553>

Mitra NJ, Nguyen A: Estimating surface normals in noisy point cloud data. In: Symposium on Computational Geometry, pp 322-328 (2003). <https://doi.org/10.1145/777792.777851>

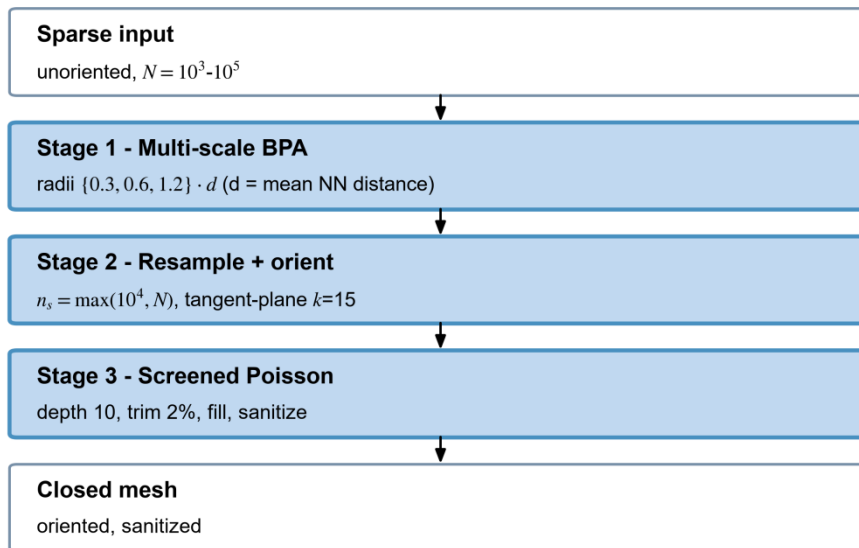


Fig. 1. Pipeline overview: multi-scale BPA with radii anchored to the measured mean nearest-neighbor distance d_{in} ; independent-per-radius pivoting with vertex-offset concatenation; area-weighted support resampling; consistent re-orientation; screened Poisson with trimming, hole filling, and sanitization.

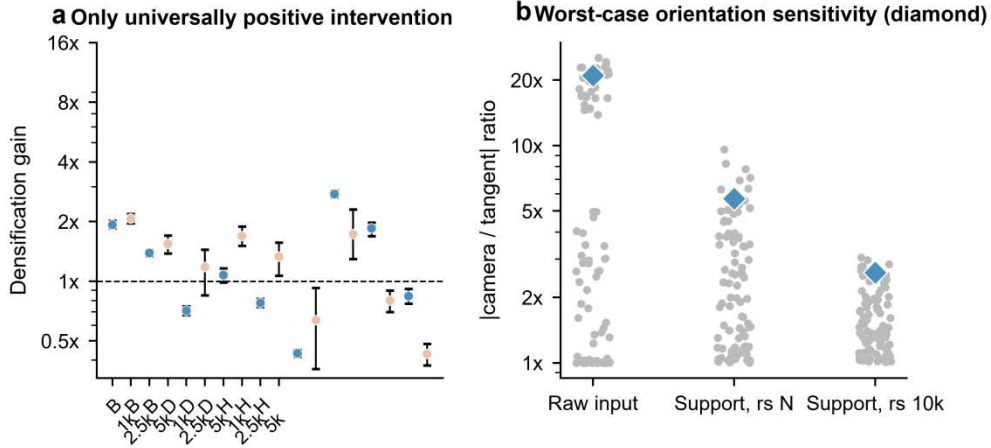


Fig. 2. Densification main effect (paired log-ratios with bootstrap 95% CIs) across the nine object–density cells under both orientation procedures (a); worst-case orientation sensitivity by condition (b).

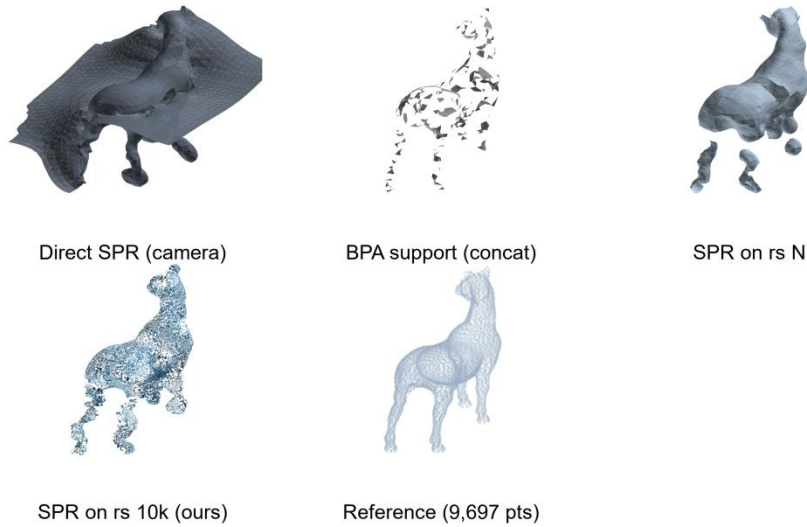


Fig. 3. Qualitative progression on horse ($N=1000$): direct SPR (camera) $\rightarrow$ BPA support $\rightarrow$ SPR on same-count resampling $\rightarrow$ SPR on dense (10k) resampling $\rightarrow$ reference point set.



Native list call: 8 triangles Independent + concat: 622 triangles

Fig. 4. The native-collapse pathology: Open3D 0.19 native list invocation (8 triangles, 11 touched vertices) vs independent-per-radius + concatenation (622 triangles) on the same input, rendered; identical vertex sets, identical vertex-based scores.

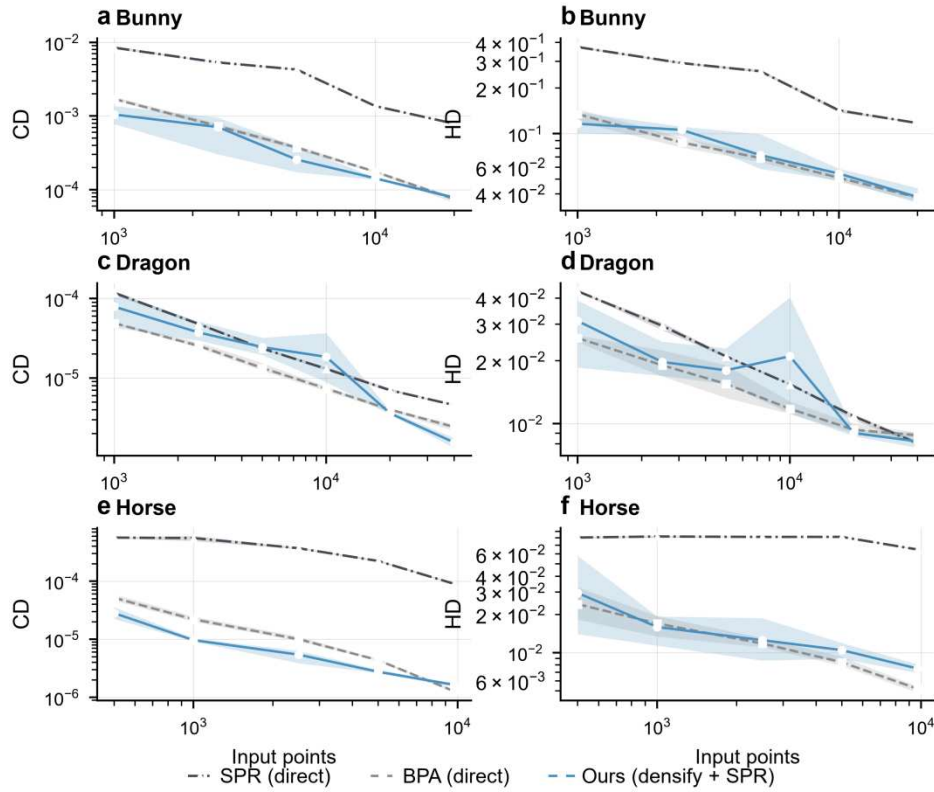


Fig. 5. Density sweeps (CD/HD95 vs input points, log-log, 10-seed bands): ours vs direct BPA vs direct SPR, supporting validation of Section 7.

Tables

Table 1. End-to-end comparison under the controlled protocol (nCD (v) / HD95 (v); mean over seeds). Config. S: N = 1,000; Config. D: near-complete inputs (bunny/dragon 20,000, horse 9,697). “-”: not available.

Cfg	Model	Ours	BPA	SPR	PGR
-----	-------	------	-----	-----	-----

Cfg	Model	Ours	BPA	SPR	PGR
S	bunny	1.05x10 ⁻³ / 0.116	1.70x10 ⁻³ / 0.135	8.46x10 ⁻³ / 0.374	–
S	dragon	7.92x10 ⁻⁵ / 0.031	4.91x10 ⁻⁵ / .026	1.18x10 ⁻⁴ / 0.043	–
S	horse	9.68x10 ⁻⁶ / .016	2.21x10 ⁻⁵ / 0.017	5.55x10 ⁻⁴ / 0.082	–
D	bunny	7.82x10 ⁻⁵ / 0.038	7.47x10 ⁻⁵ / .038	7.89x10 ⁻⁴ / 0.117	6.62x10 ⁻⁵ / .021
D	dragon	3.60x10 ⁻⁶ / .009	4.01x10 ⁻⁶ / 0.009	7.03x10 ⁻⁶ / 0.011	1.61x10 ⁻⁶ / .007
D	horse	1.65x10 ⁻⁶ / 0.007	1.28x10 ⁻⁶ / .005	9.04x10 ⁻⁵ / 0.065	–

Table 2. The factorial: nCD for raw_cam, raw_tan, raw_oracle (dagger: dragon only), rsN_cam, rsN_tan, rs10k_cam, rs10k_tan. Mean of 10 matched seeds; paired CIs in this supplement (Tables S1-S2).

Object	N	raw_cam	raw_tan	raw_oracle†	rsN_cam	rsN_tan	rs10k_cam	rs10k_tan
Bunny	1000	2.64!x! 10 ⁻³	2.64!x! 10 ⁻³	–	1.46!x! 10 ⁻³	1.48!x! 10 ⁻³	2.13!x! 10 ⁻⁴	1.89!x! 10 ⁻⁴
Bunny	2500	7.80!x! 10 ⁻⁴	7.81!x! 10 ⁻⁴	–	4.48!x! 10 ⁻⁴	4.89!x! 10 ⁻⁴	1.12!x! 10 ⁻⁴	1.06!x! 10 ⁻⁴
Bunny	5000	4.09!x! 10 ⁻⁴	4.16!x! 10 ⁻⁴	–	1.77!x! 10 ⁻⁴	1.60!x! 10 ⁻⁴	8.71!x! 10 ⁻⁵	4.88!x! 10 ⁻⁵
Dragon	1000	1.53!x! 10 ⁻³	5.12!x! 10 ⁻³	1.80!x! 10 ⁻⁴	9.97!x! 10 ⁻⁴	2.12!x! 10 ⁻³	3.40!x! 10 ⁻⁴	3.72!x! 10 ⁻⁴
Dragon	2500	3.84!x! 10 ⁻⁴	6.12!x! 10 ⁻⁴	6.40!x! 10 ⁻⁵	3.96!x! 10 ⁻⁴	9.90!x! 10 ⁻⁴	1.82!x! 10 ⁻⁴	2.48!x! 10 ⁻⁴
Dragon	5000	1.93!x! 10 ⁻⁴	2.61!x! 10 ⁻⁴	3.00!x! 10 ⁻⁵	1.99!x! 10 ⁻⁴	3.78!x! 10 ⁻⁴	1.29!x! 10 ⁻⁴	1.84!x! 10 ⁻⁴
Horse	1000	5.65!x! 10 ⁻³	3.23!x! 10 ⁻⁴	–	2.51!x! 10 ⁻³	1.01!x! 10 ⁻³	1.61!x! 10 ⁻⁴	1.26!x! 10 ⁻⁴
Horse	2500	2.14!x! 10 ⁻³	1.03!x! 10 ⁻⁴	–	7.12!x! 10 ⁻⁴	1.26!x! 10 ⁻⁴	1.14!x! 10 ⁻⁴	5.71!x! 10 ⁻⁵
Horse	5000	7.47!x! 10 ⁻⁴	4.01!x! 10 ⁻⁵	–	2.17!x! 10 ⁻⁴	5.54!x! 10 ⁻⁵	9.29!x! 10 ⁻⁵	3.62!x! 10 ⁻⁵

Table 3. Native list invocation vs independent-per-radius + concatenation, full pipeline downstream nCD.

Object	N	Concat (ours)	Native	Ratio
Bunny	1000	1.77e-04	4.02e-02	227x
Bunny	5000	5.43e-05	4.20e-03	77x
Bunny	20000	3.86e-05	8.69e-04	23x
Dragon	1000	4.02e-04	2.64e-02	66x
Dragon	5000	1.53e-04	2.41e-03	16x
Dragon	20000	1.38e-04	9.08e-04	7x
Horse	1000	1.15e-04	6.27e-02	545x
Horse	5000	3.72e-05	9.42e-02	2529x
Horse	9697	2.37e-05	1.33e-03	56x

Table 4. Parameter sensitivity at N=1000: nCD relative to the shipped configuration (triplet (0.3,0.6,1.2)d, normal radius 1x).

Radius triplet	Normal radius	Bunny	Dragon	Horse	Span
(0.2,0.5,1.0)d	0.5 imes	1.60	1.26	2.94	1.26–2.94
(0.2,0.5,1.0)d	1 imes	1.47	1.26	3.09	1.26–3.09
(0.2,0.5,1.0)d	2 imes	1.41	1.27	2.36	1.27–2.36
(0.3,0.6,1.2)d (shipped)	0.5 imes	1.53	0.86	1.08	0.86–1.53
(0.3,0.6,1.2)d (shipped)	1 imes	1.00	1.00	1.00	1.00–1.00
(0.3,0.6,1.2)d (shipped)	2 imes	0.90	1.10	1.03	0.90–1.10
(0.5,1.0,2.0)d	0.5 imes	1.38	0.54	0.78	0.54–1.38
(0.5,1.0,2.0)d	1 imes	0.88	0.65	0.81	0.65–0.88
(0.5,1.0,2.0)d	2 imes	0.53	0.62	0.79	0.53–0.79

Table 5. Mesh validity after the full method (mean over 5 seeds). “Boundary” counts edges used by exactly one face; “non-manifold” edges are used by three or more.

Object	N	Method	Watertight	Components	Boundary	Non-manifold	Faces
Bunny	1000	Direct SPR	0%	2.4	176	3.8	9k
Bunny	1000	Pipeline	0%	4.4	804	0.8	138k
Bunny	5000	Direct SPR	0%	6.4	166	20.8	36k
Bunny	5000	Pipeline	0%	3.6	870	1.8	163k
Dragon	1000	Direct SPR	0%	7.0	151	7.6	7k
Dragon	1000	Pipeline	0%	13.8	505	3.8	143k
Dragon	5000	Direct SPR	0%	26.4	205	41.8	40k
Dragon	5000	Pipeline	0%	16.8	726	10.0	170k
Horse	1000	Direct SPR	0%	5.4	186	10.0	9k
Horse	1000	Pipeline	0%	7.0	1020	0.6	125k
Horse	5000	Direct SPR	0%	9.8	238	29.8	40k
Horse	5000	Pipeline	0%	6.6	944	1.2	120k

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Sl.docx](#)