



Cornell University



Massachusetts
Institute of
Technology

Sidhanth Holalkere,¹ David S. Bindel,¹ Silvia Sellán,^{2,3} Alexander Terenin¹
¹Cornell University ²MIT ³Columbia University



COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK



Abstract

Poisson Surface Reconstruction is a widely-used algorithm for reconstructing a surface from an oriented point cloud. To facilitate applications where only partial surface information is available, or scanning is performed sequentially, a recent line of work proposes to incorporate uncertainty into the reconstructed surface via Gaussian process models. The resulting algorithms first perform Gaussian process interpolation, then solve a set of volumetric partial differential equations globally in space, resulting in a computationally expensive two-stage procedure. In this work, we apply recently-developed techniques from geometric Gaussian processes to combine interpolation and surface reconstruction into a single stage, requiring only one linear solve per sample. The resulting reconstructed surface samples can be queried locally in space, without the use of problem-dependent volumetric meshes or grids. These capabilities enable one to (a) perform probabilistic collision detection locally around the region of interest, (b) perform ray casting without evaluating points not on the ray's trajectory, and (c) perform next-view planning on a per-ray basis. They also do not require one to approximate kernel matrix inverses with diagonal matrices as part of intermediate computations, unlike prior methods. Results show that our approach provides a cleaner, more-principled, and more-flexible stochastic surface reconstruction pipeline.

Computing the Inter-domain Posterior

Posterior over Poisson equation's solution:

$$\underbrace{(f | v)(\cdot)}_{\text{posterior over solution}} = \underbrace{f(\cdot)}_{\text{prior over solution}} + \underbrace{\mathbf{K}_{f(\cdot)v}}_{\text{cross-covariance from Poisson eqn.}} \underbrace{(\mathbf{K}_{vv} + \Sigma)^{-1}(v - v(\mathbf{x}) - \epsilon)}_{\text{standard GP solve}}$$

Unknown quantities for posterior mean and covariance:

1. Cross-covariance $k_{f,v}(\cdot, \cdot') = \text{Cov}(f(\cdot), v(\cdot'))$
2. Scalar field covariance $k_f(\cdot, \cdot') = \text{Cov}(f(\cdot), f(\cdot'))$

Posterior samples: also need to jointly sample of f and v

Geometric Gaussian Processes

Key idea:

1. Assume periodic boundary conditions: lift GP to *torus* \mathbb{T}^3
2. Derive Fourier expansions of f and v to obtain covariance

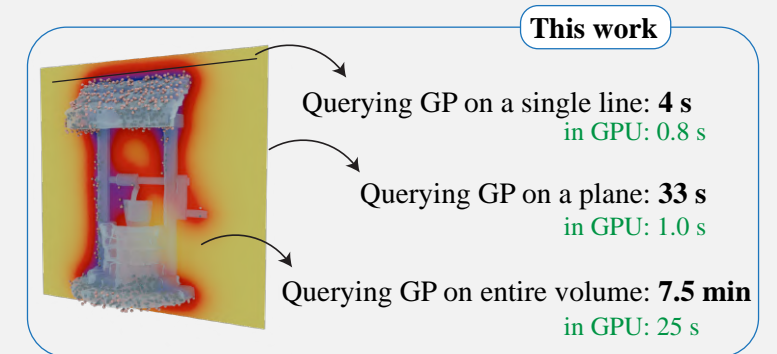
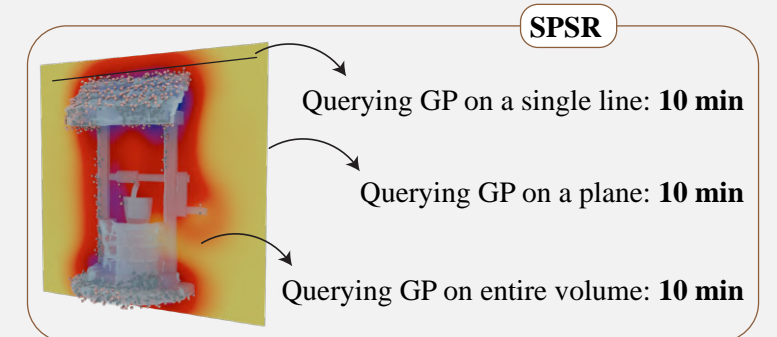
Proposition. We have

$$k_{f,v_i}(x, x') = \sum_{\substack{n \in \mathbb{Z}^d \\ n \neq 0}} \frac{n_i \sqrt{\rho_{v_i}(n)}}{\|n\|^2} \sin(n \cdot (x - x'))$$

$$k_f(x, x') = \sum_{\substack{n \in \mathbb{Z}^d \\ n \neq 0}} \frac{\sum_{i=1}^d n_i^2 \rho_{v_i}(n)}{\|n\|^4} (\sin(n \cdot x) \sin(n \cdot x') + \cos(n \cdot x) \cos(n \cdot x')).$$

See paper for Karhunen–Loève decomposition for sampling f and v

Runtime Improvement



Poisson Surface Reconstruction

Input: point cloud with surface normals

Steps:

1. Interpolate normals onto 3D finite element mesh to get v
2. Solve $\Delta v = \nabla \cdot f$ for f

Result: finite element representation of inside-outside function f

Stochastic Poisson Surface Reconstruction

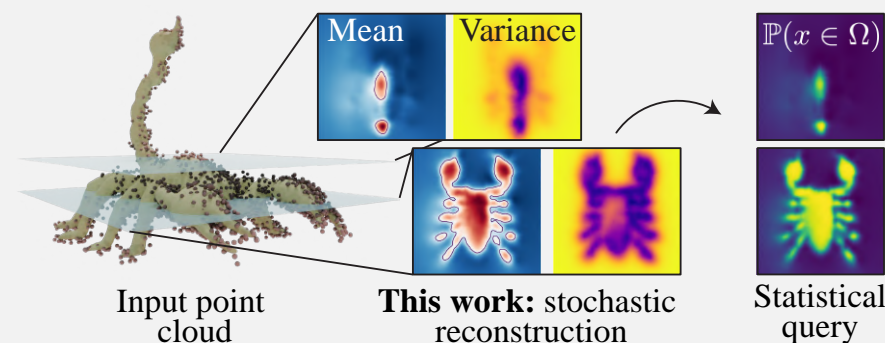
Previous work: replaces mesh interp. with Gaussian process

- + Quantifies uncertainty
- Expensive global PDE solve
- Not output-sensitive
- Inaccurate covariance approximations

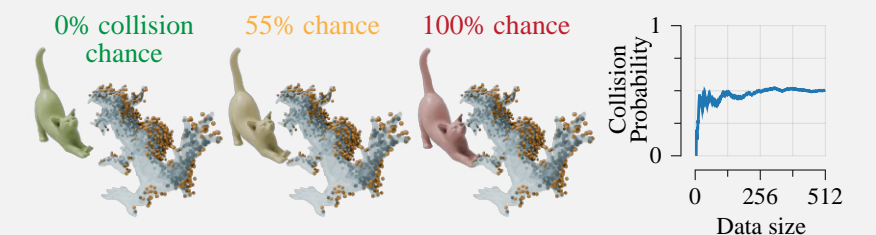
Our work: computes cross-domain posterior directly

- + Faster output-sensitive runtime
- + Accurate covariance
- + Analytic description of process
- + High-resolution sampling

Statistical Queries



Application: Collision Detection



Application: Next View Planning

