SIGGRAPH 2026 Revisiting Gaussian Process Implicit Surfaces for Uncertainty-Aware 3D Reconstruction in Robotics

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1 Introduction

Reconstructing object surfaces from point cloud observations is a fundamental problem in both computer graphics and robotics. Classical reconstruction algorithms convert point clouds into mesh representations using geometric priors or analytic formulations. More recently, implicit representations have become popular due to their ability to model complex surfaces and topologies. In particular, neural implicit representations [8] have enabled high-quality reconstructions by learning continuous functions that describe object geometry.

Despite their success, many modern reconstruction techniques assume access to large datasets or dense observations. In contrast, robotic systems typically operate with limited sensing capabilities. Robots perceive objects through sparse and noisy measurements obtained from sensors such as RGB-D cameras, LiDAR, or tactile arrays. These observations are often incomplete and must be integrated incrementally as the robot interacts with the environment.

In such settings, reconstructing the geometry alone is insufficient. Robots must also reason about the uncertainty of the reconstructed surfaces in order to plan safe interactions and guide further sensing actions. For example, regions with high uncertainty may indicate where additional observations should be collected. This motivates probabilistic surface representations that explicitly model uncertainty in geometry.

Gaussian Process Implicit Surfaces (GPIS) provide [5, 7] a natural framework for probabilistic surface reconstruction. By modeling the implicit surface function as a Gaussian process, GPIS representations produce both surface predictions and associated uncertainty estimates. This capability makes GPIS particularly attractive for robotic perception tasks involving active exploration, multi-modal sensing, and interaction with partially observed objects.

2 Gaussian Process Implicit Surfaces

Implicit surface representations describe object geometry using a function $f(\mathbf{x}) : \mathbb{R}^3 \rightarrow \mathbb{R}$ where the surface corresponds to the zero level-set $f(\mathbf{x}) = 0$. In the Gaussian Process Implicit Surface formulation, this function is modeled as a Gaussian process:

$$f(\mathbf{x}) \sim \mathcal{GP}(0, k(\mathbf{x}, \mathbf{x}'))$$

where $k(\cdot, \cdot)$ denotes a covariance function defining correlations between spatial locations.

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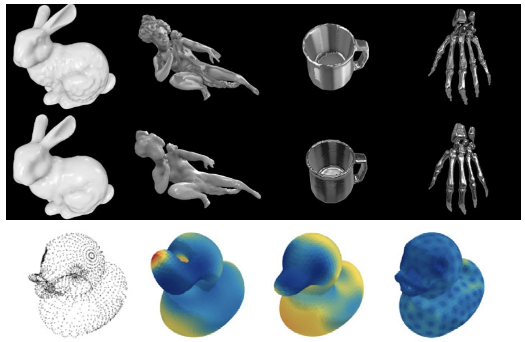

Fig. 1. Example ground truth models (the first row) and reconstructions based on our approach (the second row). Reconstruction results using different GPIS configurations (the third row).

Given a set of observed points sampled from an object's surface, GP regression is used to learn the implicit function that describes the underlying geometry. Observations are typically augmented with additional samples inside and outside the surface in order to constrain the implicit function. The resulting model produces both the mean surface estimate and predictive variance at each query location.

The predictive variance plays a crucial role in robotics applications. It quantifies uncertainty in the reconstructed geometry and can be used to guide sensing strategies. Regions with high variance correspond to poorly observed areas of the surface and may indicate where additional measurements should be collected.

However, classical GPIS methods [1] suffer from computational limitations due to the cubic complexity of Gaussian process regression. Furthermore, global GP models may smooth out fine geometric details when applied to complex shapes.

3 Combining Global and Local Surface Models

To address these limitations, we consider a reconstruction framework that combines global and local Gaussian process models[6]. The global model captures the overall geometry of the object, while local models focus on finer geometric details in spatially partitioned regions.

The reconstruction pipeline begins with a raw point cloud observation obtained from sensors such as cameras or tactile arrays. Data augmentation techniques generate additional samples inside and outside the surface to improve the stability of the implicit representation. The input point cloud is then partitioned using a spatial data structure such as an octree, producing several local regions of interest.

For each region, a local Gaussian process model is trained using the corresponding subset of observations. During inference, predictions from local and global models are combined based on their predictive uncertainty. For a given query point, the prediction with lower variance is selected, enabling the model to preserve detailed local geometry while maintaining global consistency.

This hybrid formulation improves reconstruction fidelity Fig 1 while retaining the probabilistic properties of the GPIS representation. Moreover, the use of spatial partitioning enables parallel training of local models, improving computational scalability.

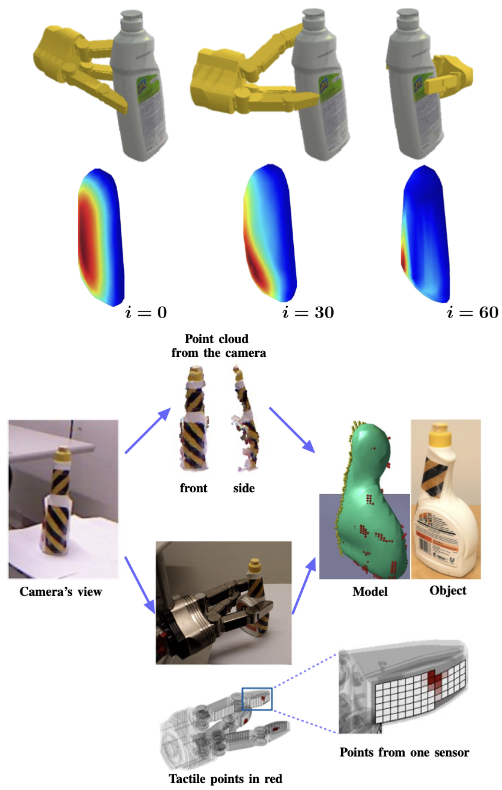

Fig. 2. Surface evolution during grasp explorations (the first row). An example model formed based on the point cloud (in yellow) from the camera and the contact points (in red) using a real robot.

4 Applications in Robotic Perception

Probabilistic surface reconstruction is particularly valuable in robotic perception tasks that involve interaction with partially observed objects[1, 3]. One example is tactile exploration, where robots iteratively touch object surfaces to infer shape. In such scenarios, GPIS uncertainty estimates can guide the robot toward regions where additional measurements are most informative.

Another application is robotic grasp planning[4]. Accurate surface geometry is necessary for identifying stable grasp configurations, but uncertainty information is equally important for avoiding risky interactions. By modeling uncertainty explicitly, GPIS-based reconstructions enable robots to reason about confidence in predicted surfaces. Similar representations can also be used to model robot morphology to plan actions [2].

Finally, probabilistic surface models provide a natural framework for integrating multiple sensing modalities. Visual observations from cameras can be combined with tactile measurements collected during physical interaction Fig 2. The Gaussian process formulation supports such data fusion by incorporating observations from different sources within a unified probabilistic model.

5 Discussion and Future Directions

Recent advances in neural implicit representations have significantly improved the quality of surface reconstruction in graphics applications. However, many of these methods focus primarily on geometric fidelity and do not explicitly model uncertainty. In contrast, probabilistic approaches such as GPIS offer complementary capabilities that are particularly relevant for robotics and physical AI systems. Future directions include advancing the scalability [5] and expressive power of GPIS to enable high-fidelity, uncertainty-aware reconstruction systems that seamlessly integrate into graphics pipelines and robotic perception workflows. We believe that revisiting probabilistic implicit surfaces in the context of modern geometric learning offers promising opportunities for developing more robust and interactive 3D reconstruction methods.

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