Implicit representation priors meet Riemannian geometry for Bayesian robotic grasping

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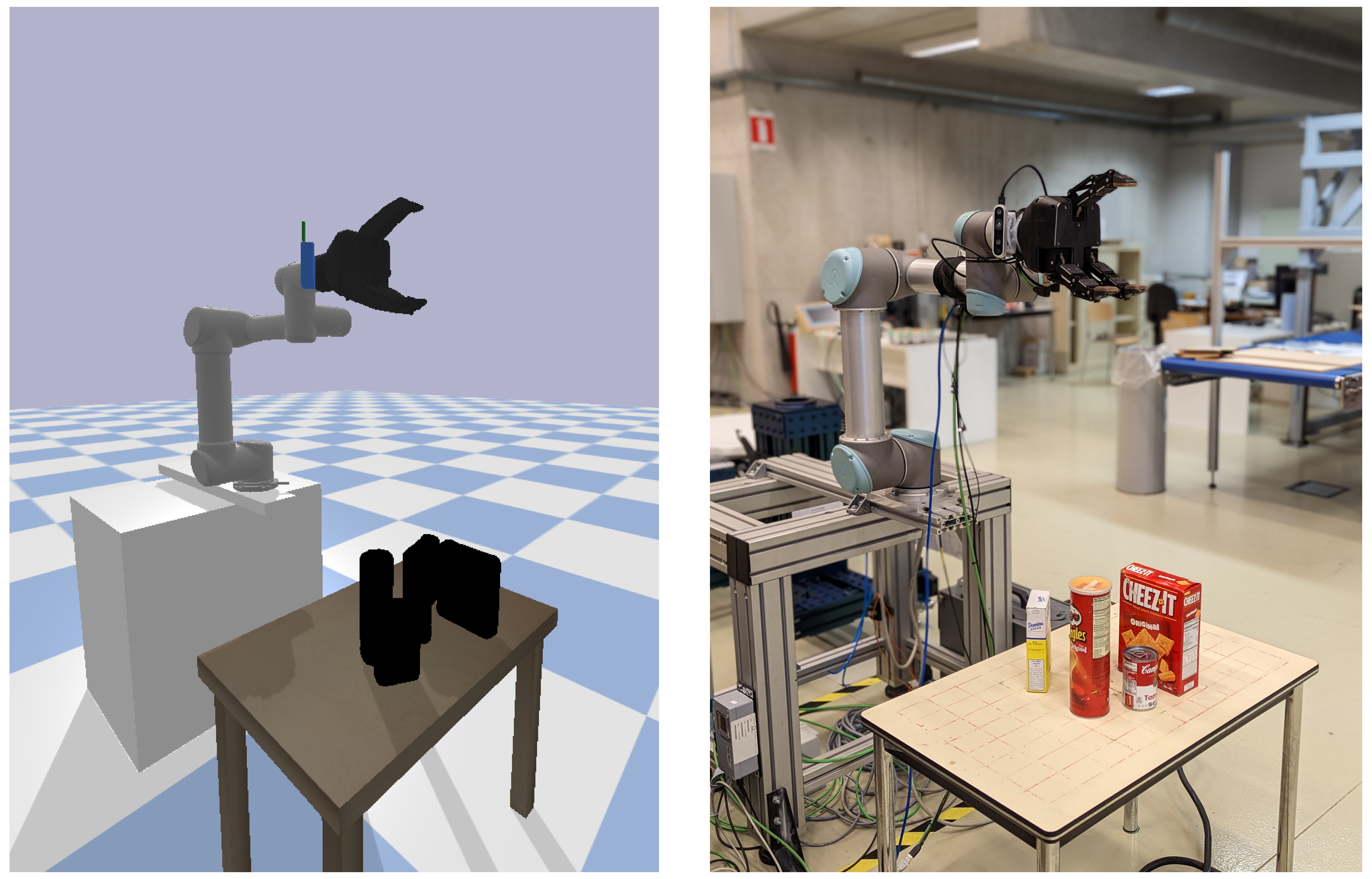
Robotic grasping



We formulate the problem of grasping as the Bayesian inference of the hand configuration $\mathbf{h} := (\mathbf{x}, \mathbf{q})$ that is a posteriori the most likely given a successful grasp $S = 1$, an occupied point o and a point cloud $\mathbf{P}$.

Probabilistic modeling

We solve the grasping problem by computing the maximum a posteriori

$$\mathbf{h}^* = \arg\max_{\mathbf{h}} \; p(\mathbf{h}|S=1, o=1, \mathbf{P})$$

From the Bayes rule, the posterior of the hand configuration is

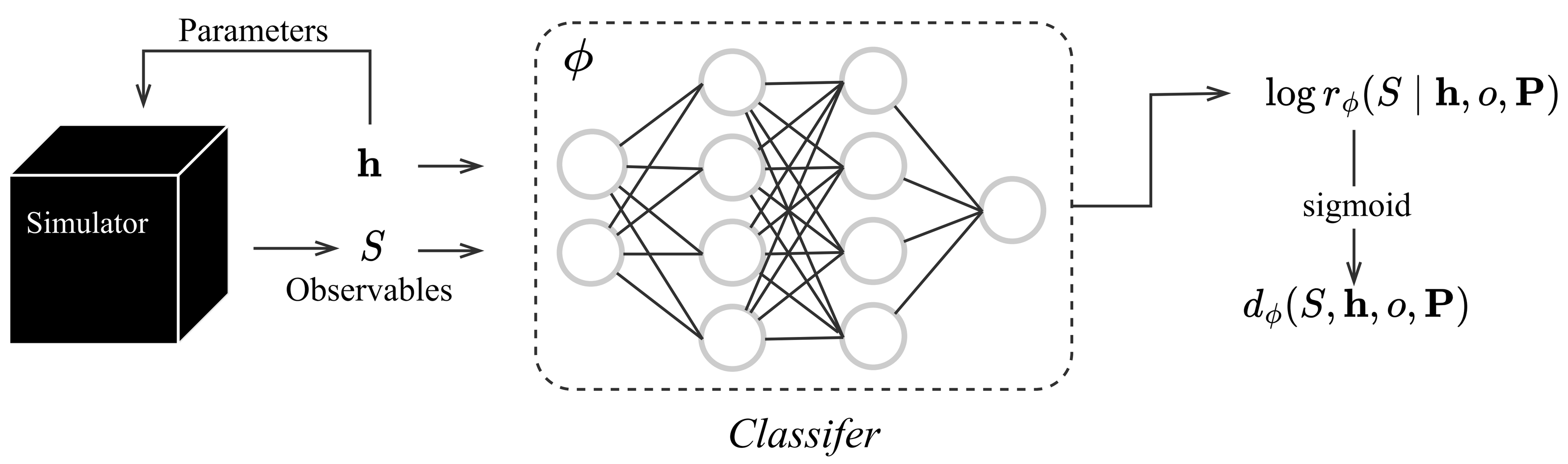
$$p(\mathbf{h} \mid S, o, \mathbf{P}) = \frac{p(S \mid \mathbf{h}, o, \mathbf{P})}{p(S \mid o, \mathbf{P})} p(\mathbf{h} \mid o, \mathbf{P})$$

which can be rewritten as the product of the likelihood-to-evidence ratio r and a scene-dependent prior

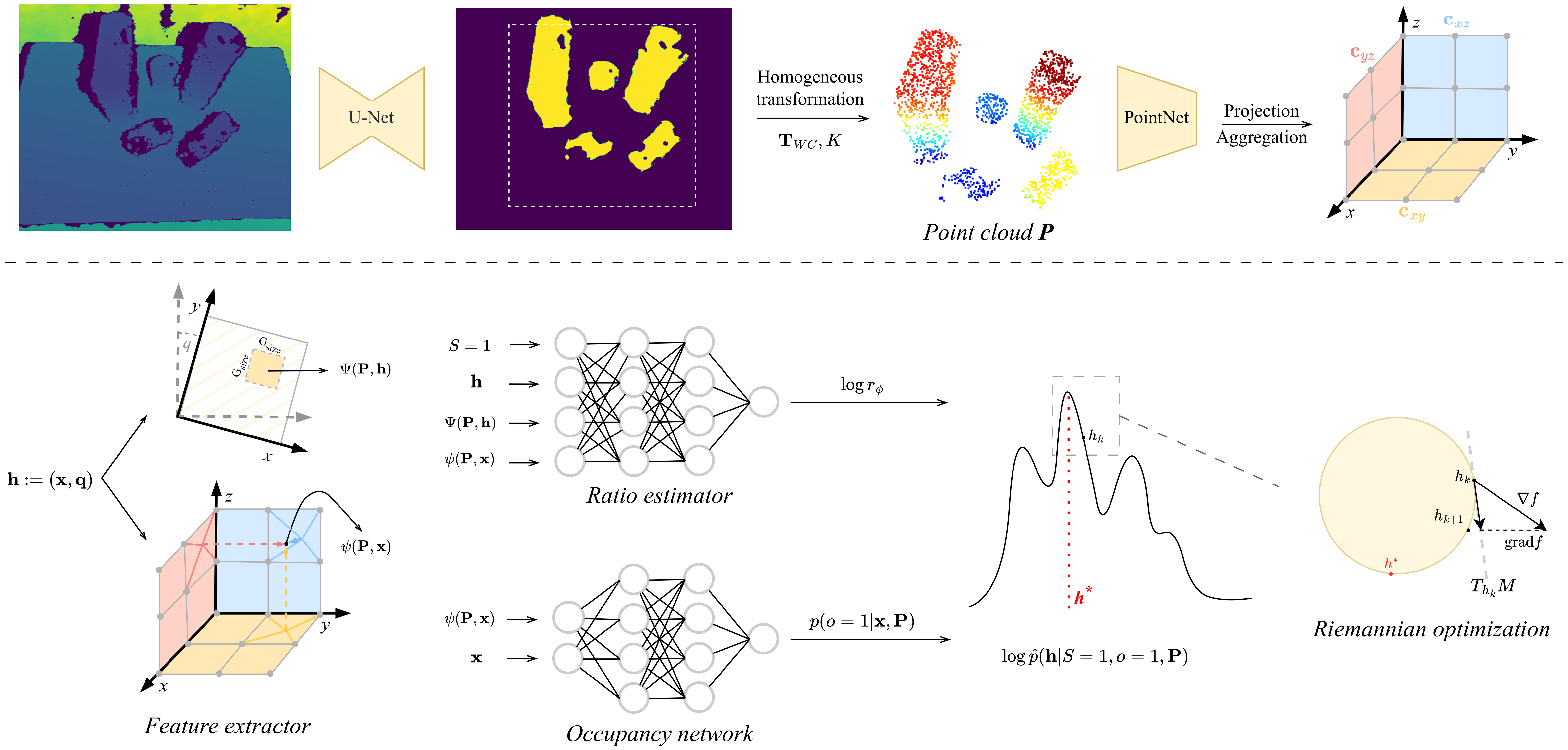
$$p(\mathbf{h}|S, o, \mathbf{P}) = r(S \mid \mathbf{h}, o, \mathbf{P}) p(\mathbf{h} \mid o, \mathbf{P}).$$

Neural Ratio Estimation

Neural ratio estimation consists in training a classifier d_ϕ to discriminate between samples from the joint density, $p(S, \mathbf{h} \mid o, \mathbf{P})$, and the marginal densities, $p(S \mid o, \mathbf{P})p(\mathbf{h} \mid, o, \mathbf{P})$.

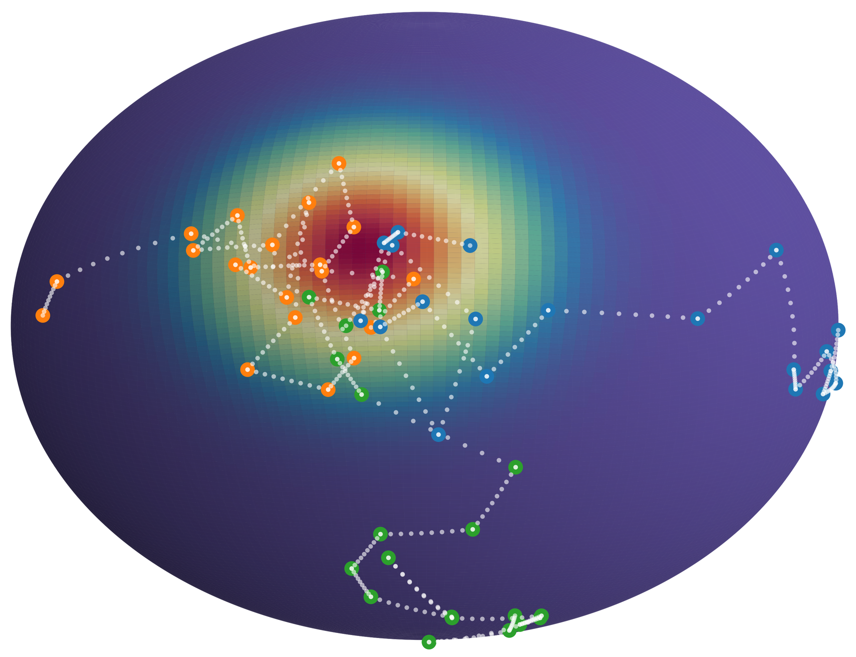


Grasp inference pipeline

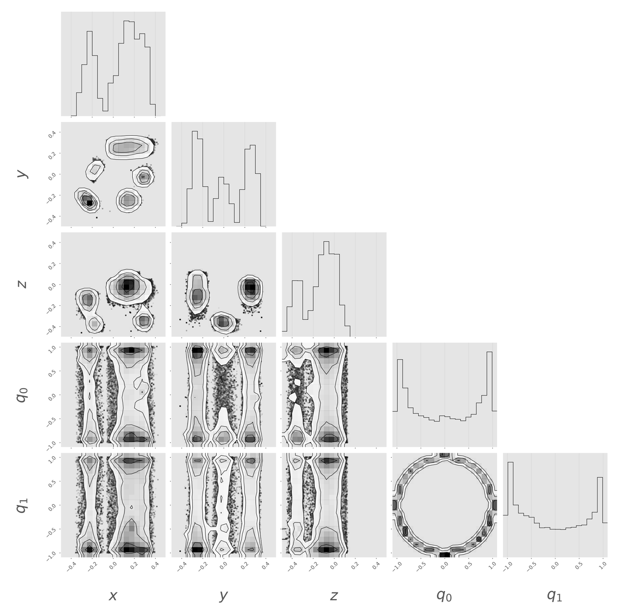


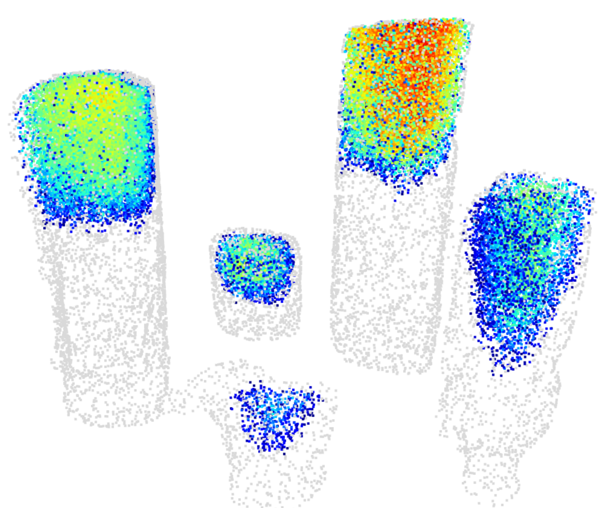
Manifold sampling

By integrating likelihood-free Hamiltonian Monte Carlo and geodesic Monte Carlo, we are able to sample from the posterior density defined on a smooth manifold using a closed-form geodesic.



Approximate posterior





Experimental results

Method	Success rate (%)	% cleared
Simulation results		
GPD	73.7	72.8
VGN ($\varepsilon = 0.95$)	91.5	79
VGN ($\varepsilon = 0.9$)	87.6	80.4
VGN ($\varepsilon = 0.85$)	80.4	79.9
Ours	91.1	77
Real-world results		
Ours	95.6	88

Take-home messages

- Our implicit prior captures relevant 3D information about the scene, enabling full Bayesian inference for complex tasks.
- Our approach directly models variables on their respective manifolds, effectively handling intrinsic constraints.
- Our approach overcomes the simulation-real-world discrepancy without performance degradation.

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