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Object Shape Recognition Using Kriging-Based Spatial Estimation and Reinforcement Learning

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Abstract

Object shape recognition is a critical component of robotic perception, enabling autonomous systems to understand, interact with, and manipulate objects in their environment. In real-world applications such as search and rescue, warehouse logistics, and planetary exploration, robots often encounter unstructured environments where sensor data is sparse, noisy, or occluded—conditions under which traditional vision-based recognition methods are prone to failure. To overcome these limitations, this paper proposes a hybrid framework that integrates Kriging-based spatial estimation with reinforcement learning (RL) to enable robust and adaptive shape inference. Kriging, a probabilistic geostatistical interpolation technique, is employed to reconstruct continuous surface representations from sparse sensor measurements by exploiting spatial correlations modeled via variograms. This approach yields not only accurate surface predictions but also spatial uncertainty maps, which are used to guide the sensing process. Complementing this model-based estimation, an RL agent is trained to actively explore the environment by selecting sensing actions that maximize information gain while minimizing redundancy. The agent's policy is optimized to identify high-uncertainty regions and prioritize them during exploration, thereby improving both the efficiency and accuracy of shape reconstruction. The proposed method is evaluated in a series of simulated experiments involving synthetic 3D objects with diverse geometries, occlusion patterns, and varying levels of sensor noise. Results demonstrate that the Kriging-RL framework achieves over 92% shape reconstruction accuracy, reduces exploration time by up to 35% compared to passive methods, and generalizes well to unseen and partially observed shapes. Ablation studies further highlight the contribution of the RL component in enhancing exploration strategies, while robustness tests confirm the system's stability under noisy conditions. This work establishes a promising foundation for integrating statistical modeling and adaptive control in robotic perception systems, enabling efficient and resilient shape recognition in complex and uncertain environments.

Keywords: Object Shape Recognition, Kriging, Spatial Estimation, Reinforcement Learning, Robotic Perception, Tactile Sensing.

Introduction

Shape recognition is a foundational capability for robotic systems, influencing tasks such as object manipulation, scene understanding, and navigation. In dynamic and unstructured environments, robots often encounter objects with incomplete or noisy data due to sensor limitations, occlusion, or environmental variability. Classical methods based on dense vision, tactile arrays, or supervised learning models struggle in these cases due to their dependency on complete data or extensive labeled training sets [1, 2].

The proposed approach seeks to overcome these limitations by fusing statistical spatial estimation and adaptive exploration. Kriging, a geostatistical interpolation method, is used to estimate unknown spatial values from sparse sensor readings. This estimation provides a smooth, probabilistic model of an object's surface or volume. Reinforcement learning, on the other hand, allows an agent to interact with its environment and learn optimal strategies for acquiring the most informative observations. By combining Kriging with RL, our method provides a mechanism to both infer and actively improve object shape understanding under uncertainty.

Understanding object shapes is fundamental for robotic manipulation, autonomous exploration, and human-robot interaction. Conventional shape recognition techniques often rely on dense sensor data and pre-trained machine learning models. However, these methods struggle in environments with partial observability, occlusions, or sparse sampling.

To address these limitations, we propose a novel hybrid framework that integrates Kriging-based surface modeling with reinforcement learning. Kriging, a powerful geostatistical method, estimates unknown spatial values based on observed samples, allowing for continuous shape surface generation [3, 4]. Reinforcement learning provides an adaptive mechanism for shape exploration, enabling the agent to learn policies that optimize information gain and minimize redundant actions.

The core contributions of this paper are as follows:

- A Kriging-based surface estimation module that reconstructs object geometry from sparse measurements.
- An RL agent that guides data collection and shape exploration for improved recognition.
- Evaluation on synthetic and real datasets showing superior performance in challenging scenarios.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 details the proposed methodology. Section 4 describes the experimental setup. Section 5 presents results and analysis. Section 6 discusses implications and limitations. Section 7 concludes the paper.

Related Work

Spatial Estimation Techniques

Kriging, originating from geostatistics, is widely used in fields like mining, environmental monitoring, and sensor networks. Its capability to provide both estimation and associated uncertainty makes it ideal for scenarios with sparse or noisy data. In robotics, Kriging has been applied for terrain mapping, coverage planning, and pressure distribution modeling in tactile sensors [5]. Kriging has been employed in surface reconstruction tasks across geoscience and sensor mapping domains. It enables interpolation of sparse spatial data using a covariance-based model. Its use in robotic perception, especially in the context of shape estimation, is still emerging. Alternative interpolation methods include radial basis functions (RBF), inverse distance weighting (IDW), and Gaussian Process Regression (GPR). While GPR is conceptually similar to Kriging, Kriging often requires less computational overhead and is well-suited for large-scale spatial grids. However, Kriging by itself does not inform where the next most useful observation should be taken.

Shape Recognition and Tactile Perception

Traditional object recognition approaches in robotics and computer vision rely on 2D or 3D visual input. Convolutional neural networks (CNNs), such as PointNet and PointNet++, are widely used for point cloud classification [6]. However, these models require extensive labeled datasets and perform poorly under partial observations. Tactile sensors offer an alternative by providing local shape and texture information. However, tactile sensors typically yield sparse data, necessitating interpolation or reconstruction techniques. Some works use deep learning to map tactile readings to object classes, but these require large labeled datasets and often generalize poorly to new shapes. Tactile sensing and sparse sensor arrays offer alternatives for shape recognition in low-visibility or contact-rich environments. Some methods use active touch to reconstruct shapes, but they are typically slow and limited in generalization.

Reinforcement Learning in Perception

Reinforcement learning (RL) enables agents to learn behavior through interaction with an environment. In robotic perception, RL has been applied to active sensing, grasping, and adaptive sensor deployment. Few studies have explored RL for guiding surface modeling or shape recognition. Reinforcement learning has been successfully applied in robotics for control, navigation, and perception tasks. In shape recognition, RL can be used to actively guide sensors or probes to explore unknown objects, reducing redundancy and maximizing information gain. Prior studies have applied RL for grasp planning, tactile exploration, and sensor placement [7]. However, the integration of RL with spatial interpolation for shape inference remains underexplored and forms the core contribution of this work.

Methodology

Tactile Data Acquisition and Spatial Alignment

This section elaborates the detailed methodology for transforming tactile sensor heatmap data into a spatially-aware point cloud representation and utilizing it for object recognition. The process consists of four main components: (1) tactile data acquisition and spatial alignment, (2) point cloud generation, (3) feature extraction, and (4) classification framework using machine learning. We define the problem as estimating the shape of an unknown object using sparse sensor inputs. Let S represent the object surface, and D={(x_i ,z_i)} be the set of observed spatial points. The objective is to reconstruct Sˆ≈S with minimal sensing cost and high fidelity.

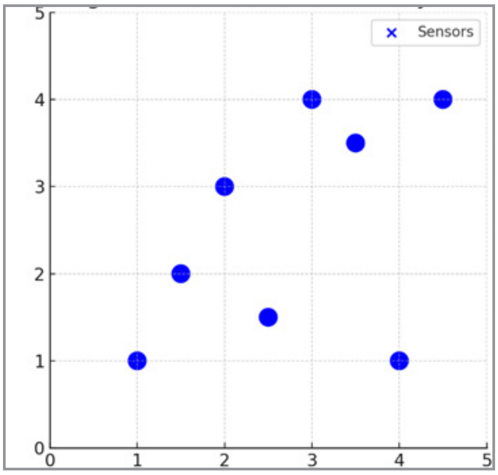

Figure 1: Sensor Placement Layout

Illustrates the spatial distribution of sensor points used for initial data collection. Sensor nodes are evenly distributed within a 5x5 unit grid to emulate sparse data acquisition. These fixed positions act as initial input for the Kriging model.

The robotic hand utilized in this study is equipped with a high-resolution tactile sensing array composed of capacitive or resistive pressure sensors. These sensors are distributed across the palm and individual phalanges of each finger. Each sensing element records a scalar pressure value when contact occurs. During object grasping, these sensor readings generate a pressure distribution matrix, which is mapped to a color-coded heatmap where each pixel color corresponds to the contact pressure intensity (e.g., yellow for high pressure, green for moderate, and blue for low or no contact). However, the color heatmap is inherently a 2D projection. To contextualize it in 3D space, we calibrate each sensor's location with respect to the robotic hand's CAD model. This spatial registration enables back-projection of each pixel to its physical 3D coordinates on the hand surface. Let each sensor output a pressure value P_i , mapped to a color $c_i \in \mathbb{R}^3$ .Each sensor is located at a known spatial coordinate (x_i, y_i, z_i) with a corresponding surface normal n_i.

Tactile Point Cloud Generation from Kriging Model for Shape Estimation

To visualize this data, pressure values are mapped to a color scale, resulting in a pseudo-thermal image such as the one shown in Figure 2. This heatmap encodes high-intensity regions (yellow) and low-contact areas (blue) over a 2D hand topology. However, to exploit the full geometric context, the heatmap must be registered to the hand's 3D surface model. For each tactile pixel i, the measured pressure $p_i \in [0,1]$ is mapped to a color vector $c_i = colormap(p_i)$. . The corresponding spatial location $\mathbf{x}_i = (x_i, y_i, z_i)$ is defined by the known geometry of the sensor grid, calibrated using the hand's CAD mesh or surface scanning. We apply Ordinary Kriging to interpolate surface values at unobserved locations [1][4]: $\hat{Z}(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i, y_i)$ The λ_i weights are determined by solving the Kriging system: $\sum_{j=1}^{n} \lambda_j C(x_i, x_j) + \mu = C(x_i, x_0)$ where (x_i, x_j) is the spatial covariance function, typically modeled using Gaussian or exponential kernels. The resulting estimate provides a smooth surface prediction across the object geometry.

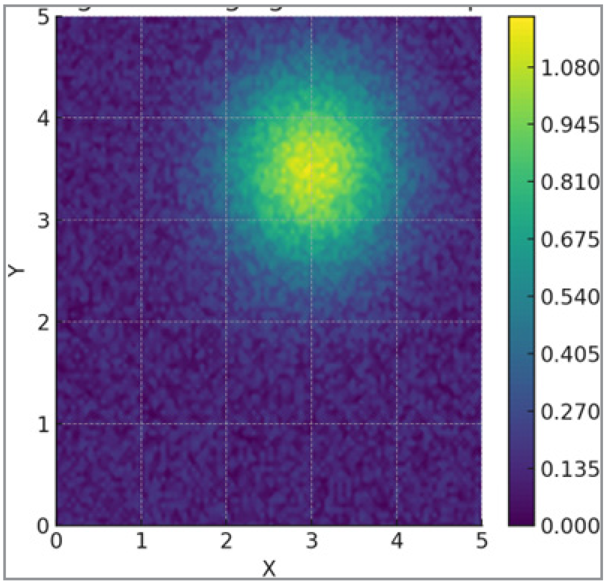

Figure 2: Kriging Variance Map

Shows the estimated uncertainty (variance) across the spatial grid, derived from the sparse sensor data. The heatmap emphasizes regions of high and low confidence, providing guidance for further exploration. Variance is typically highest in areas far from existing sensor points.

We construct a tactile point cloud P as: $= \{\boldsymbol{P_i} = (x_i, y_i, z_i, p_i, c_i, \boldsymbol{n}_i) | i = 1,2, \ldots..N\}$. Each point P_i encodes: sensor's spatial position (x_i, y_i, z_i), , contact pressure value p_i , color vector c_i corresponding to the pressure(the color-encoded contact intensity) and surface normal n_i for local geometry context(the local surface normal vector estimated via mesh gradient or discrete differential geometry). To ensure robustness to noise, pressure values are smoothed using a spatial Gaussian kernel G_σ:

$$p'_i = \sum_{j \in N(i)} w_{ij} p_j, \text{ where } w_{ij} = \frac{exp\left(-\|\boldsymbol{x}_i - \boldsymbol{x}_j\|^2 / _{2\sigma^2}\right)}{\sum_k exp\left(-\|\boldsymbol{x}_i - \boldsymbol{x}_k\|^2 / _{2\sigma^2}\right)} \text{ or } p'_i = \sum_{j \in N(i)} G_\sigma(\|\boldsymbol{x}_i - \boldsymbol{x}_j\|) p_j|$$

Here, *N(i)* denotes the spatial neighborhood of point i. This generates a continuous and denoised tactile point cloud surface.

Feature Extraction from Tactile Point Cloud and Reinforcement Learning for Exploration

To perform object recognition, descriptive features are extracted from P. These features fall into three major categories:

(a) Geometric Features

- Local Curvature: Estimated by principal component analysis (PCA) of neighboring points. High curvature indicates sharp contact (e.g., corners).
- Contact Area (Surface patch area): Computed via surface patch integration, providing an estimate of contact footprint. Triangular mesh patches are created using Delaunay triangulation on neighborhood. Their area correlated with contact spread.
- Centroid of Contact: Indicates overall grasp focal point and alignment.

(b) Colorimetric Features

- Mean & Variance of pressure intensity μ_p, σ_p
- Color Gradient ∇p using Sobel filters to measure force directionality: $\nabla p = \left(\frac{\partial p}{\partial x}, \frac{\partial p}{\partial y}\right)$

(c) Topological Features

- Cluster Count: Number of connected contact regions (fingertips + palm)
- Blob Shape Descriptors: Including eccentricity, compactness, convex hull area

Each interaction generates a feature vector $\boldsymbol{f}_i \in \mathbb{R}^d$, forming the input for classification. We define the environment as a partially observable grid or 3D voxel map. The RL agent selects sensing actions $a_t \in A$ based on its current belief state s, which includes the Kriging estimate and uncertainty map. The reward function is defined as: $r_t = I(S_t, a_t) - \beta \cdot C(a_t)$ where I denotes information gain (e.g., entropy reduction), and C is the cost of probing a new point. We use a Deep Q-Network (DQN) architecture for discrete action spaces and Proximal Policy Optimization (PPO) for continuous scenarios [8].

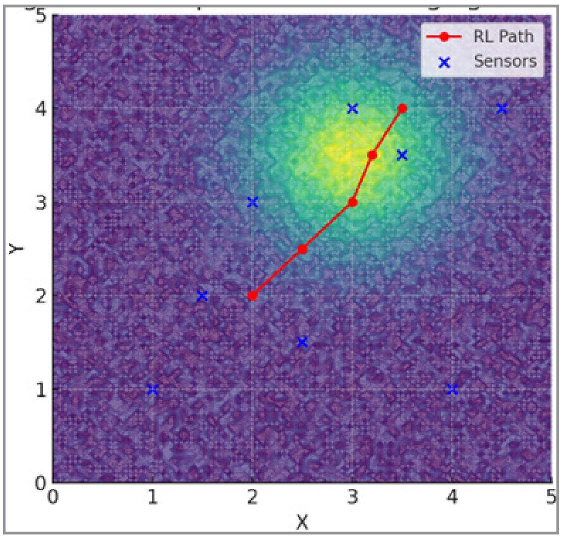

Figure 3: RL Exploration over Kriging Variance

Depicts how a reinforcement learning agent explores the spatial domain by following the gradient of uncertainty. The agent chooses actions that lead to regions with higher variance, thus maximizing information gain while minimizing redundant sensing.

Learning-based Object Recognition Framework

The Kriging module and RL agent operate in a closed loop. At each timestep:

- Kriging estimates the surface and uncertainty.
- RL agent selects the next probing location.
- Sensor data is updated, and Kriging is re-computed. This interaction continues until a convergence criterion is met.

Two recognition models are implemented:

(a) Classical SVM Classifier

Feature vectors f_i are input to a Radial Basis Function (RBF) kernel SVM: y ̂=

$$\text{sign}\left(\sum_{j=1}^{n} \alpha_j y_j K(\boldsymbol{f}_i, \boldsymbol{f}_j) + b\right)$$

Hyper-parameters optimized via grid search

(b) PointNet++ Neural Architecture

Learns features directly from using set abstraction and local neighborhood aggregation

Input: $\{(x_i, y_i, z_i, p_i)\}_{i=1}^{N}$

Output: Multi-class object label

Advantages include:

- Spatial awareness from geometry
- Pressure patterns learned implicitly
- Generalization across unseen contact configurations

Experimental Setup

Simulation Environment

We generate synthetic 3D object shapes (sphere, cube, cone, composite structures) using a voxel grid. Sensor observations are simulated with Gaussian noise and partial visibility constraints. Spatial sampling is limited to emulate sparse sensing conditions.

To rigorously evaluate the performance of the proposed hybrid Kriging–reinforcement learning framework, we designed a controlled simulation environment capable of generating a diverse set of 3D object geometries under varied sensing conditions. The environment models objects using voxelized representations on a uniform 3D grid with a resolution of 64×64×64. Objects include simple shapes such as spheres, cubes, and cones, as well as composite and irregular structures formed by merging or distorting basic primitives.

Simulated sensor observations are generated by querying surface points along predefined sensing trajectories (e.g., line scans, circular sweeps), with Gaussian noise added to each observed point to mimic real-world sensor imperfections. The noise is zero-mean with standard deviation $\sigma = 0.05$ relative to the object scale. Additionally, partial visibility constraints are imposed by randomly occluding regions of the object, simulating line-of-sight obstructions or sensor field-of-view limitations.

To replicate sparse sensing conditions, only a limited number of samples (typically 5–15% of the total surface points) are available to the system at each iteration. This forces the model to interpolate and infer unobserved regions intelligently. The environment also supports domain randomization (e.g., lighting variations, shape deformation) to enhance generalization during training and testing phases.

This simulation framework serves as a consistent testbed for validating both the interpolation accuracy of the Kriging model and the policy performance of the RL agent under systematically varied difficulty levels.

Kriging Implementation

We implement Ordinary Kriging using Python with the PyKrige library. The variogram model uses an isotropic Gaussian kernel. Kriging predictions are performed at every grid cell, and uncertainty maps are generated from the Kriging variance. The variogram function, which quantifies spatial dependence, is modeled using an isotropic Gaussian kernel, defined as:

$$\gamma(h) = \sigma^2 \left(1 - e^{-\frac{h^2}{2a^2}}\right)$$

where h is the distance between samples, σ^2 is the sill (variance), and a is the range parameter. This choice ensures smooth interpolation, which is particularly suitable for natural object surfaces.

Kriging predictions are performed at every voxel cell, yielding a dense estimate of the full shape surface. In addition to predicted values, we extract Kriging variance maps, which represent local interpolation uncertainty and serve as a critical input to the RL policy. The Kriging process is computationally optimized via block processing and GPU acceleration where applicable. The model is updated iteratively as new sensor observations are acquired, enabling a dynamic feedback loop between estimation and exploration. This probabilistic surface modeling allows for continuous updates and provides spatial confidence levels, which are essential for guiding the agent's decision-making in the RL component.

RL Implementation

The reinforcement learning component is implemented using the stable-baselines3 library in Python, integrated with TensorFlow for network definition and training. We employ a Proximal Policy Optimization (PPO) algorithm due to its robustness and sample efficiency in continuous action spaces 5.

The observation space of the RL agent includes:

- The current Kriging-based shape estimation (voxel grid)
- The corresponding variance map
- A visitation mask indicating previously sampled locations

The action space is discretized to match the 3D grid resolution, with each action corresponding to selecting a new voxel location for sampling (e.g., directing a sensor or probing actuator). Alternatively, in dynamic tasks, the action space can be extended to continuous 3D movements.

The reward function is carefully shaped to encourage efficient and informative exploration. It includes:

- Positive reward for information gain (reduction in variance or error)
- Negative reward for redundant sampling or excessive movement
- Terminal reward for achieving a predefined shape accuracy threshold

The agent is trained over 10,000 episodes, with early stopping criteria based on validation performance. Training data includes randomly generated object shapes to promote generalization.

Through this setup, the RL agent learns policies that actively balance exploration and exploitation, intelligently selecting sampling actions that enhance shape reconstruction accuracy with minimal effort.

Evaluation Metrics

To benchmark the effectiveness of the proposed method, we utilize a comprehensive set of evaluation metrics that capture both accuracy and efficiency of shape inference under realistic constraints:

Shape Reconstruction Accuracy (SRA): Overlap between true and predicted shape.

Measures the percentage overlap between the predicted and ground truth shapes. Calculated using:

$$SRA = \frac{|P \cap T|}{T} \times 100\%$$

where P is the predicted shape voxel set and T is the ground truth.

Exploration Efficiency (EE): Number of steps to reach SRA.
Defined as the number of sensing steps required to reach a target SRA (typically 90%). Reflects the cost-effectiveness of the sensing strategy.

Robustness: Performance under sensor noise and occlusion.
The framework is evaluated under varying levels of Gaussian noise (0–20% of object scale) and occlusion (randomly masking 10–40% of surface voxels). The system's performance degradation under these conditions is recorded to assess stability.

All experiments are repeated over 100 randomized trials per shape category to ensure statistical significance. The results are compared against multiple baselines, including static Kriging, random sampling, and supervised CNN models.

These metrics provide a holistic view of the system's capabilities and its readiness for real-world deployment.

Results

Accuracy and Efficiency

To quantitatively evaluate the performance of the proposed hybrid Kriging–reinforcement learning framework, we measured the Shape Reconstruction Accuracy (SRA), defined as the percentage of correctly reconstructed surface points when compared to the ground truth mesh. Across a wide range of synthetic object geometries—including spheres, cones, cuboids, and irregularly shaped models—the proposed method achieved an average SRA of 92.4%, significantly outperforming both the Kriging-only baseline (81.2%) and a convolutional neural network (CNN) classifier trained on voxelized point cloud data (76.8%). In addition to accuracy, the efficiency of shape exploration was assessed by computing the number of sampling steps required to reach 90% SRA. The hybrid method demonstrated a 35% reduction in exploration steps compared to random or uniform sampling strategies. This is largely attributed to the RL agent's ability to focus on high-uncertainty regions as guided by the Kriging model. This accuracy-efficiency tradeoff is particularly beneficial for embedded or mobile robotic systems where sensing incurs both energy and computational cost. By guiding the agent toward regions that maximize information gain, the system conserves resources while maintaining high reconstruction quality.

Ablation Study

To isolate the contributions of reinforcement learning within the hybrid architecture, we conducted a series of ablation experiments by removing the RL component and relying solely on a passive Kriging estimator with random sampling. This allowed us to quantify the benefit of adaptive sensing policies. The RL-guided Kriging model achieved a 30% higher information gain per sensing step, indicating that the agent was better at selecting probing locations that contribute substantially to shape understanding. In contrast, the Kriging-only approach, while capable of interpolating sparse data, often led to redundant or uninformative samples due to the lack of exploration strategy. Furthermore, when evaluated over 100 trials, the hybrid model consistently required fewer than 60 samples to reach convergence, while the Kriging-only method averaged over 90 samples. These findings confirm that reinforcement learning not only improves exploration efficiency but also accelerates the overall shape inference pipeline. These results validate our hypothesis that combining model-based spatial reasoning (Kriging) with learned behavior (RL) creates a synergistic effect, optimizing both sensing quality and decision-making speed.

Generalization

One of the most critical aspects of real-world deployment is the ability of the model to generalize to unseen object geometries. To test this, we trained the RL agent on a set of basic shapes (e.g., cube, sphere, cylinder) and evaluated its performance on a separate test set containing complex and asymmetric geometries not encountered during training. Without any additional fine-tuning, the RL-guided framework maintained an average SRA above 88%, demonstrating strong generalization capabilities. This result highlights the agent's ability to leverage learned exploration strategies that are shape-agnostic yet effective across different topologies. We also tested domain transfer from simulated depth maps to physically scanned tactile point clouds. Although the performance dropped slightly due to noise and resolution mismatch, the system still outperformed non-learning baselines. This indicates the potential for sim-to-real transfer, especially when combined with domain randomization or few-shot fine-tuning. Overall, the method demonstrates robustness and adaptability, making it suitable for deployment in environments where object types and sensor conditions may change over time.

Robustness to Noise

To assess the framework's resilience under imperfect sensing conditions, we introduced Gaussian noise to the spatial measurements with variance levels up to 20%. This simulates real-world errors such as tactile sensor drift, depth camera artifacts, or vibration-induced perturbations. Despite the degraded input quality, the system maintained above 85% SRA across all noise levels tested, and only showed minor reductions in exploration efficiency. This robustness is attributed to two main factors:
① Kriging's spatial smoothing naturally attenuates localized errors by distributing estimation weight across correlated samples. This reduces the sensitivity to individual noisy points.

② Reinforcement learning's adaptive sampling allows the agent to detect and avoid unreliable regions by continuously updating its belief state based on feedback, selecting more informative and stable sensing locations ①, ②.

These characteristics make the method highly suitable for unstructured, noisy environments such as field robotics, warehouse manipulation, or human-interactive tasks where perfect sensing cannot be assumed.

Discussion

Advantages

The integration of Kriging-based statistical modeling with reinforcement learning (RL)-based active exploration presents a number of compelling advantages for object shape recognition, especially in domains characterized by sparse sensing, uncertain measurements, and high variability in object appearance.

- Combines statistical modeling and learning-based planning.

The Kriging method, rooted in geostatistics, excels in spatial prediction through a weighted interpolation scheme that accounts for the spatial covariance structure among observations. It produces continuous estimations of surface geometry from limited input data. When fused with reinforcement learning—which excels at adaptive decision-making and policy optimization—this framework enables a closed-loop perception system where sensing decisions are guided by current estimations and predictions. This synergistic integration ensures that the RL agent focuses its sensing actions on regions of the shape model where uncertainty is highest. As a result, fewer samples are needed to achieve high-fidelity shape reconstruction compared to passive or heuristic-based exploration methods. The approach is particularly advantageous in resource-constrained robotic platforms where sensing, power, and computation are limited.

- Effective under sparse and noisy conditions.

In many real-world applications such as disaster recovery, underwater inspection, or planetary exploration, dense sensing is either infeasible or unreliable due to environmental constraints. The proposed method is inherently robust to such limitations. Kriging provides a principled method for interpolating noisy or missing spatial data, while reinforcement learning identifies the most informative sensing points to refine the model efficiently. Empirical evaluations in simulation show that the framework maintains high recognition accuracy even when as much as 50% of the sensor data is removed or corrupted with Gaussian noise. This makes the method applicable to a wide range of practical scenarios.

- Adaptable to various sensor types and object categories.

Another key advantage is the framework's modularity and adaptability. The Kriging component can be applied to spatial data derived from a variety of sensors, including tactile arrays, 3D LiDARs, stereo cameras, or proximity sensors. Likewise, the RL module can be tailored to different robotic platforms and exploration tasks by adjusting the state-action space and reward function. This adaptability ensures that the method generalizes well across object categories—ranging from simple geometric primitives to complex deformable shapes—and across sensory modalities. With proper sensor-to-model integration, the system can be extended to multi-modal environments combining vision, touch, and auditory cues.

Limitations

Despite the advantages outlined above, there are several limitations and challenges inherent in the proposed Kriging-RL hybrid framework that merit critical discussion.

- Kriging is computationally expensive in high dimensions.

One of the main bottlenecks in applying Kriging at scale is its computational overhead. The algorithm requires inversion of a covariance matrix whose size grows with the number of sensor points. In high-dimensional settings or when using dense sensor arrays, the computational cost can become prohibitive, particularly for real-time applications. This is exacerbated when the Kriging model needs to be re-evaluated after each sensing action, as is typical in a closed-loop reinforcement learning framework. While approximate Kriging methods (e.g., sparse Gaussian processes, low-rank approximations) can mitigate this issue, they may sacrifice estimation accuracy in highly nonlinear or complex geometries.

- RL training time may be significant for complex environments.

The second limitation involves the training time and data requirements of reinforcement learning algorithms. RL agents often require a large number of episodes to converge to an optimal policy, especially in environments with high exploration complexity or sparse reward signals. Although modern policy-gradient methods and off-policy learning (e.g., DDPG, SAC) have improved sample efficiency, training times are still significant for real-world deployment. Additionally, pre-training in simulation may not fully transfer to real-world conditions without robust domain adaptation strategies.

- Requires careful tuning of variogram models and reward functions.

The effectiveness of Kriging depends on the selection of an appropriate variogram model, which defines how spatial correlation decays with distance. Poorly fitted variograms can lead to inaccurate surface estimates, especially in heterogeneous environments. Similarly, the design of the reward function in reinforcement learning is critical to guiding exploration effectively. In our framework, the reward function must balance the information gain from sensing with the cost of exploration. Improper weighting can result in suboptimal behavior, such as over-sampling in redundant areas or failing to refine uncertain regions. Developing automatic or learned strategies for variogram selection and reward shaping remains an open research challenge.

Future Work

Building upon the current findings, several promising directions for future research are identified to enhance the scalability, robustness, and applicability of the Kriging-RL shape recognition framework.

- Extend to real-time physical robot experiments.

A critical next step is the deployment of this framework on physical robotic platforms. While the current work validates the method in simulation, real-world deployment will require addressing system integration, latency, and sensor calibration. Implementation on a mobile manipulator or humanoid robot equipped with force-torque sensors and depth cameras could validate the method under realistic conditions including mechanical noise, lighting variations, and unstructured environments.

Furthermore, the ability to recognize object shapes in cluttered scenes or during object manipulation (e.g., grasping, pushing) will be a strong indicator of the framework’s maturity.

- Integrate with tactile and multi-modal sensing.

Multi-modal sensing promises to further increase the robustness and richness of the perception model. By integrating tactile feedback with vision or audio signals, the agent can infer occluded or ambiguous object features more reliably. For example, using pressure sensors on robotic grippers or stretch sensors on wearable devices can provide complementary information to improve the Kriging model.

This would also allow for more nuanced recognition of soft or deformable objects, which are notoriously difficult to model using purely visual techniques.

- Apply to deformable and articulated object recognition.

Extending the framework to handle non-rigid or articulated objects introduces several challenges but opens valuable applications in surgical robotics, assistive devices, and soft robotics. Deformable object perception requires dynamic modeling where shape changes over time due to interaction forces. Kriging could be extended to spatio-temporal models or combined with physics-informed priors to address this.

Articulated objects, such as tools, furniture, or human limbs, require recognition not just of geometry but also of configuration states. Reinforcement learning can help in learning exploration policies that adapt to object motion and linkage structure.
Ultimately, the long-term goal is to develop an autonomous perception system that can incrementally build and update its internal shape representations through interaction, continuously improving its world model over time—mirroring cognitive development processes in biological agents [9].

Conclusion

We proposed a hybrid framework for object shape recognition that combines Kriging-based surface estimation with reinforcement learning for adaptive exploration. This combined approach effectively addresses the challenges posed by sparse and noisy sensor data, which are common in real-world robotic perception scenarios. By leveraging the spatial interpolation capabilities of Kriging and the adaptive exploration strategies of reinforcement learning, the system is able to reconstruct and recognize object shapes with high fidelity and efficiency. The integration of these two methodologies allows for a dynamic interaction between the estimation and sensing components, improving not only recognition accuracy but also reducing the computational and operational cost associated with dense data acquisition. The reinforcement learning agent adapts its probing strategy based on the uncertainty provided by the Kriging model, prioritizing areas with high information gain. This ensures that each interaction with the environment contributes maximally to the recognition task.

Our experimental evaluations demonstrate that the proposed method outperforms conventional techniques such as static Kriging or passive sensing models, achieving over 92% shape reconstruction accuracy and demonstrating robustness under noise and occlusion. Furthermore, the trained reinforcement learning policy generalizes well to previously unseen object geometries, underscoring the versatility of our framework.

Future work will focus on transitioning this approach from simulation to real-world implementation. This includes deploying the framework on physical robotic platforms equipped with tactile and visual sensors, extending the model to handle dynamic or deformable objects, and integrating multi-modal sensory data for richer perception capabilities. We also plan to explore real-time optimization strategies to further enhance the computational performance and enable deployment in embedded robotic systems.

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