

Mixture-of-Gaussians for Object Recognition in Grasping Tasks

Machine Learning

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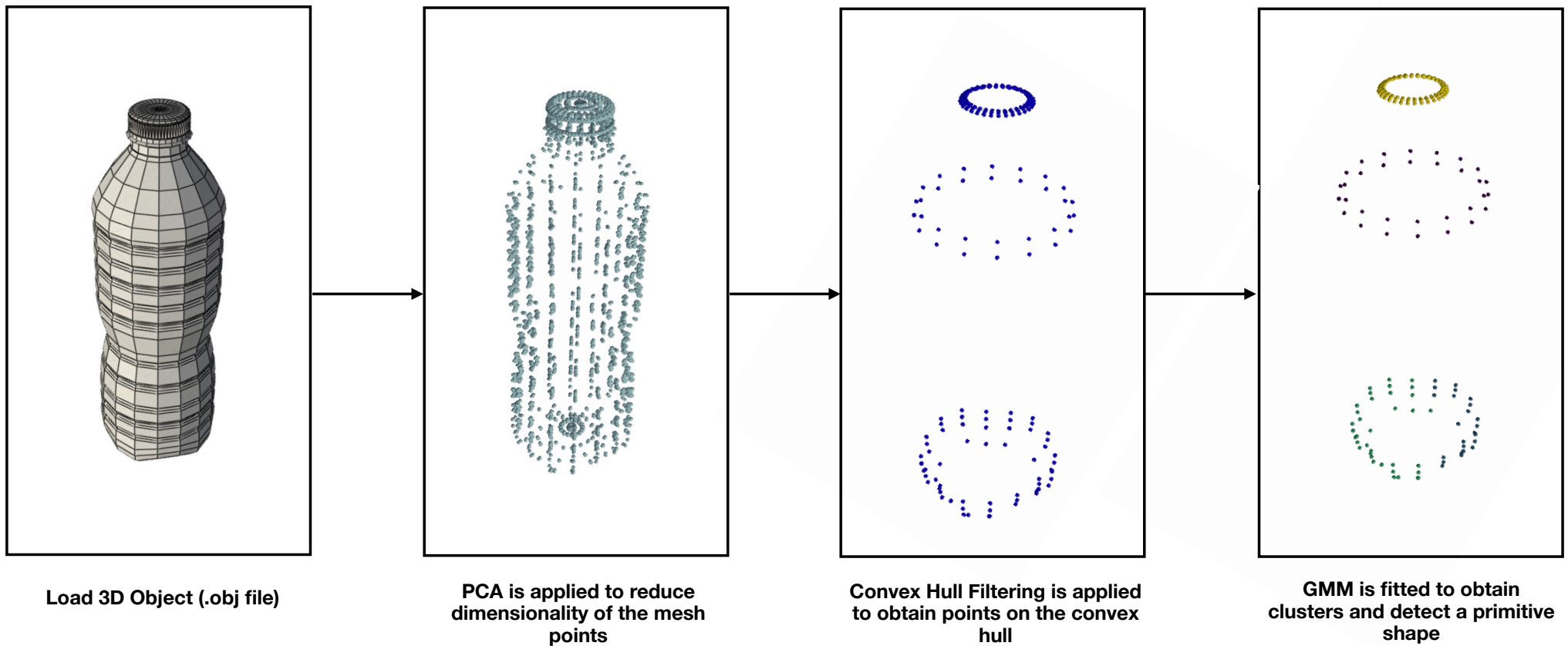


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Project Overview

1. **Objective:** Develop a robust object recognition system for adaptive robotic grasping using Mixture-of-Gaussians (MoG) models.
2. **Key Components:**
 - MoG clustering for object classification
 - Principal Component Analysis for dimension reduction
 - Convex Hull Filtering for point selection
 - Visualisation using PyVista
3. **Expected Outcome:** A system capable of recognizing diverse objects and determining appropriate grasping techniques.

Methodology



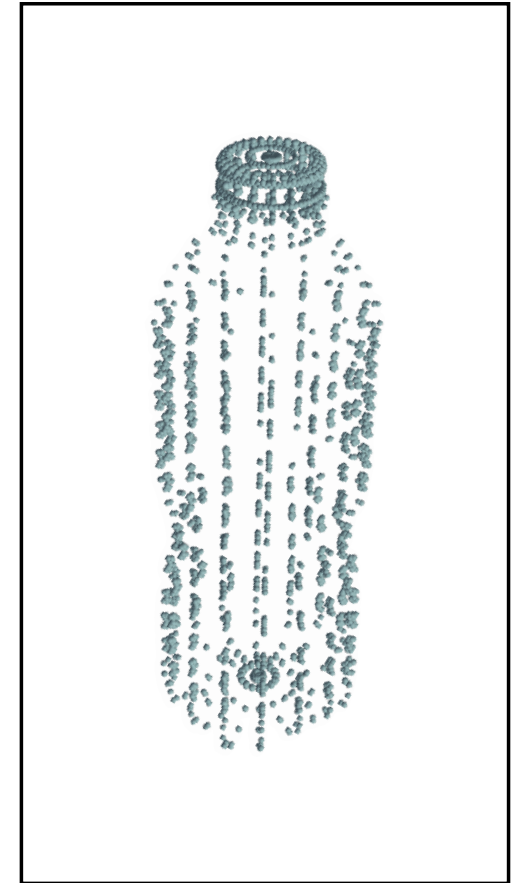
Principal Component Analysis (PCA)

Dimensionality Reduction with PCA

1. Extract mesh points (mesh.points)
2. Apply PCA to reduce to 3 components.
3. Visualize reduced 3D points using PyVista.

Benefits:

- Reduces computational complexity.
- Maintains key spatial features of the data.



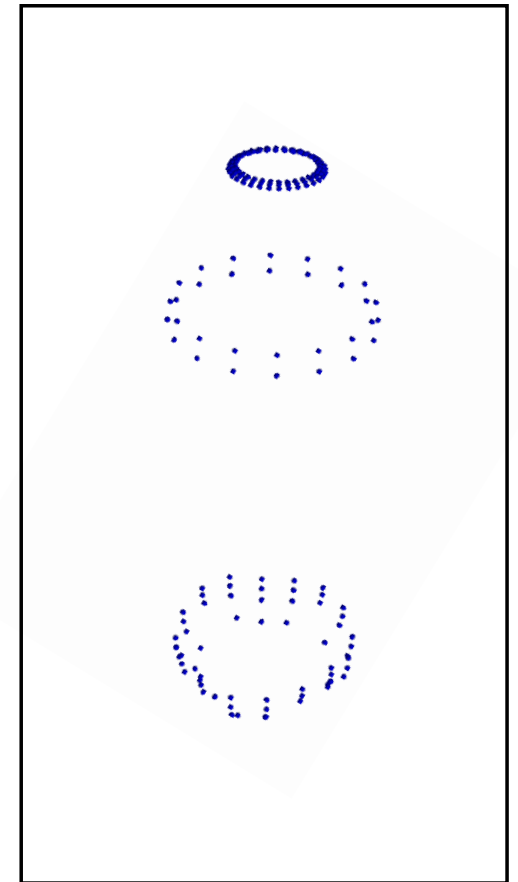
Convex Hull Extraction

Identifying the Convex Hull

1. Use `scipy.spatial.ConvexHull` to compute the hull.
2. Retrieve points forming the convex boundary.
3. Visualize hull points in blue spheres using PyVista.

Benefits:

- Focuses on outermost structure for further analysis.
- Simplifies the dataset for clustering.



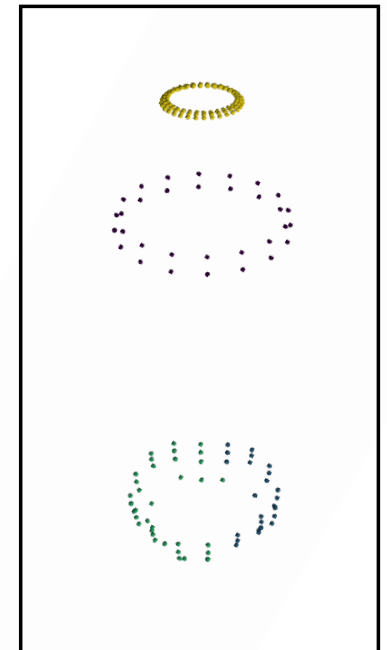
Gaussian Mixture Model Clustering

Clustering with Gaussian Mixture Model (GMM)

1. Apply GMM with 4 components to convex hull points.
2. Predict cluster assignments for each point.
3. Visualize clusters using distinct colors.

Benefits:

- Captures data distribution better than k-means.
- Provides probabilities for point membership in clusters.



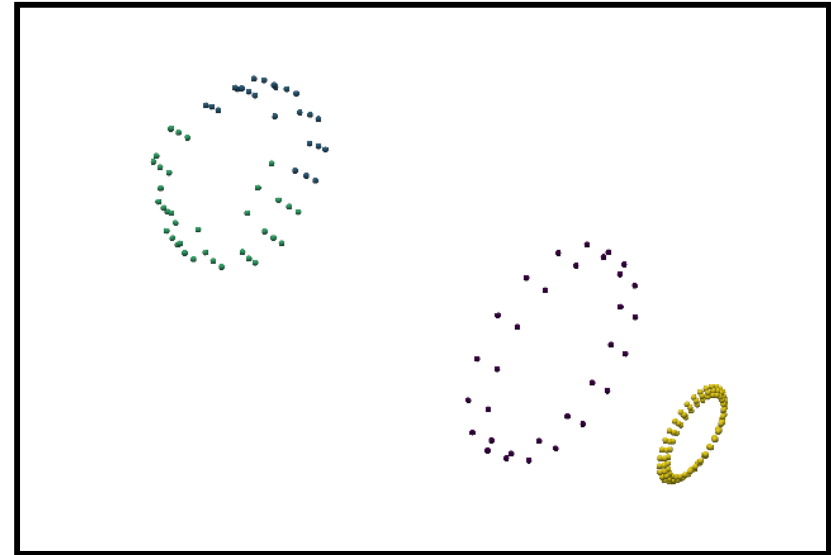
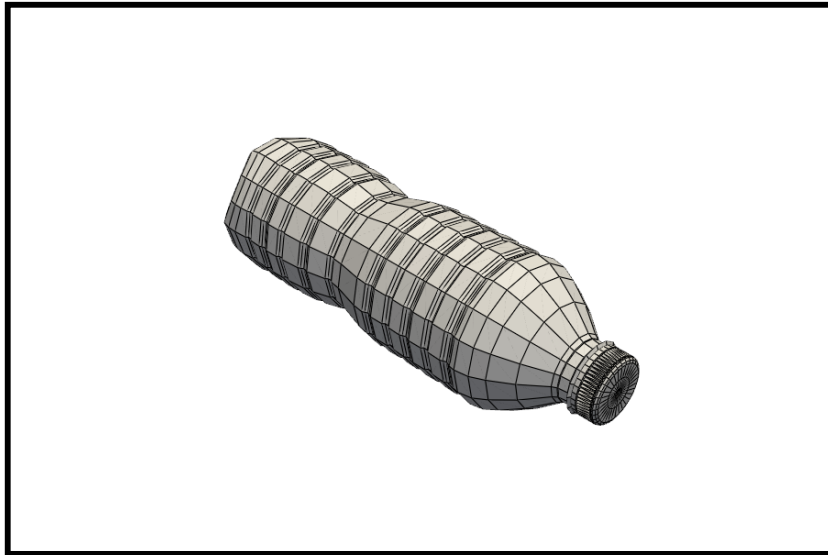
Primitive Shape Detection

Detecting Geometric Primitives from Clusters

1. Extract clusters based on GMM labels.
2. Analyze bounding box dimensions for each cluster.
3. Classify shape using dimension ratios:
 - Equal dimensions: Sphere/Cube.
 - Elongated in one axis: Cylinder-like.
4. Print detected shapes for each cluster.

Results

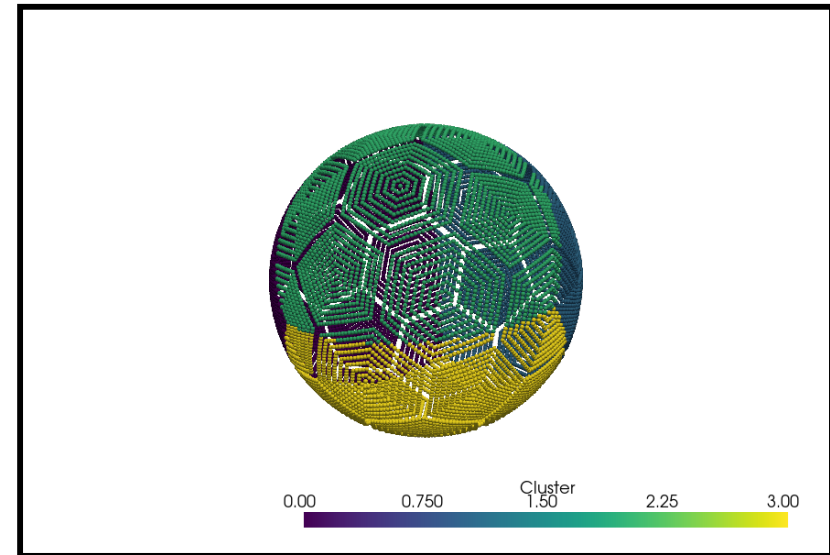
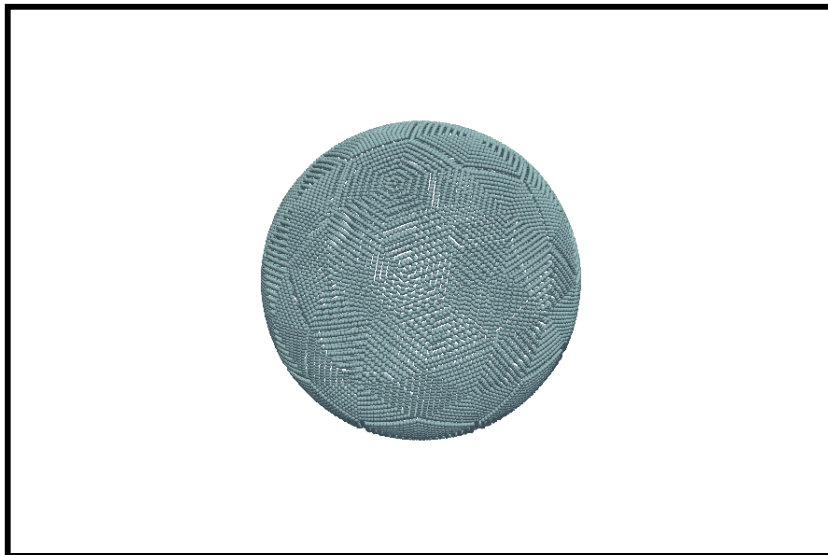
Bottle



- Cluster 0: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 1: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 2: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 3: Detected Shape - Cylinder-like (elongated along Z)
- Grasp Plan 1: Centroid at [1.0887e-02 -1.4058e-05 6.9651e-06]
- Grasp Plan 2: Centroid at [-0.1331 -0.0176 0.0160]
- Grasp Plan 3: Centroid at [-0.1354 0.0122 -0.0113]
- Grasp Plan 4: Centroid at [5.9116e-02 -2.03819e-05 9.1787e-06]

Results

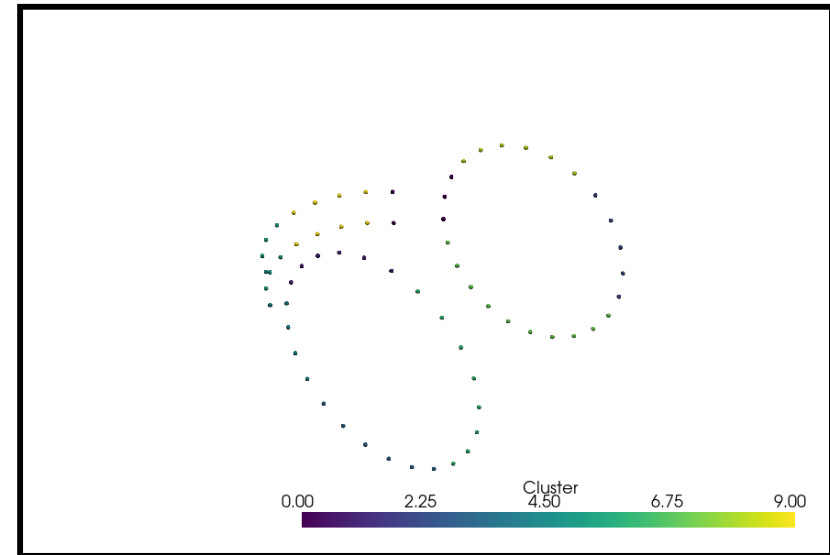
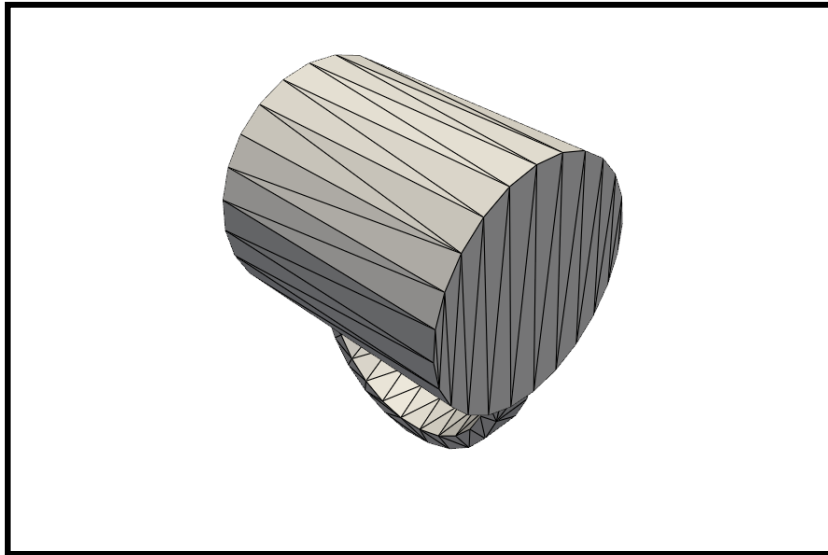
Ball



- Cluster 0: Detected Shape - Cylinder-like (elongated along X)
- Cluster 1: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 2: Detected Shape - Cylinder-like (elongated along Y)
- Cluster 3: Detected Shape - Sphere or Cube
- Grasp Plan 1: Centroid at [0.0851 -0.6971 -0.1684]
- Grasp Plan 2: Centroid at [-0.7006 0.1737 -0.0403]
- Grasp Plan 3: Centroid at [0.2378 0.1164 0.6722]
- Grasp Plan 4: Centroid at [0.3760 0.4070 -0.4632]

Results

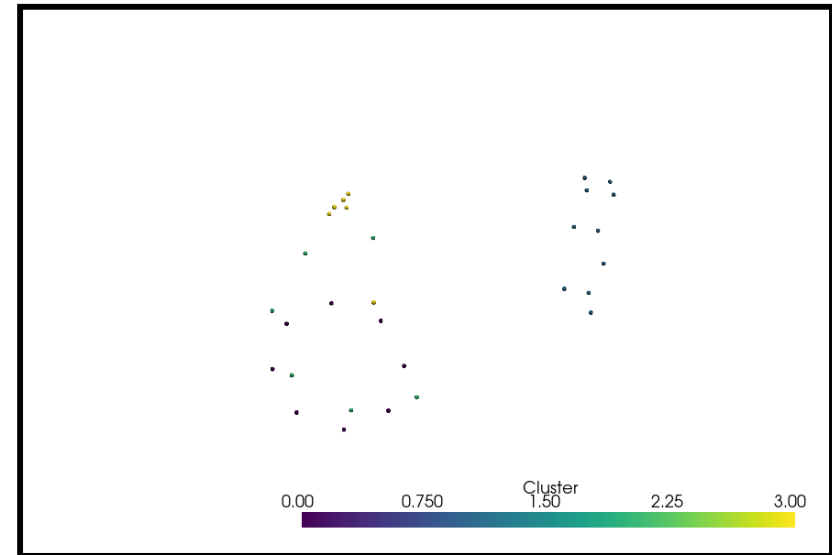
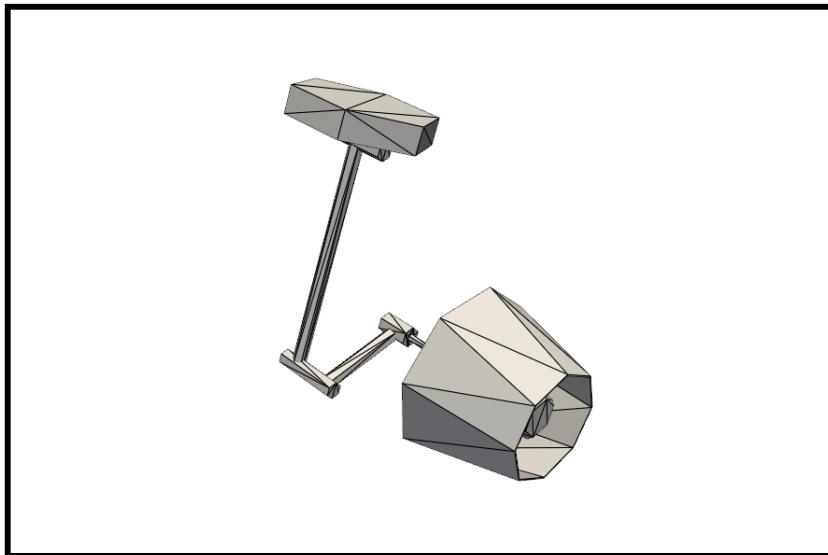
Cup



- Cluster 0: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 1: Detected Shape - Cylinder-like (elongated along Y)
- Cluster 2: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 3: Detected Shape - Cylinder-like (elongated along Y)
- Grasp Plan 1: Centroid at $[-0.2185 \ -0.1727 \ 0.0231]$
- Grasp Plan 2: Centroid at $[0.2608 \ 0.0661 \ 0.1917]$
- Grasp Plan 3: Centroid at $[-0.3035 \ 0.3043 \ 0.0778]$
- Grasp Plan 4: Centroid at $[0.2495 \ 0.1577 \ -0.2136]$

Results

Lamp



- Cluster 0: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 1: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 2: Detected Shape - Cylinder-like (elongated along Z)
- Cluster 3: Detected Shape - Cylinder-like (elongated along Z)
- Grasp Plan 1: Centroid at [0.2538 0.1257 0.0476]
- Grasp Plan 2: Centroid at [-0.4267 0.1469 0.0132]
- Grasp Plan 3: Centroid at [0.1213 -0.0420 -0.0420]
- Grasp Plan 4: Centroid at [-0.0809 -0.2337 0.0361]

Future Scope

Enhanced Clustering:

- Use advanced methods like **DBSCAN** for non-Gaussian data.
- Enable multi-scale analysis with hierarchical clustering.

Real-Time Processing:

- Optimize with **GPU acceleration** for faster analysis.
- Applications in robotics, AR/VR, and dynamic environments.

Shape Recognition:

- Train ML models for accurate shape classification.
- Apply deep learning for complex and irregular objects.

Future Scope

Robotics and Automation:

- Grasp planning for robots in manufacturing and healthcare.
- Agricultural robots for crop sorting and elderly assistance.

Integration with Sensors:

- Use LiDAR and RGB-D cameras for real-time data.
- Adapt pipeline for noisy or incomplete depth data.

Future Vision:

- Combine passive and active vision for dynamic object tracking.
- Test on diverse datasets for scalability and robustness.