Approach and Algorithm Description

1. Objective

The task is to estimate the normal angle and visible area of the largest visible face of a rotating cuboidal box at each timestamp, and to compute the axis of rotation vector with respect to the camera frame.
Depth images of the cuboid are recorded using a wall-mounted depth camera, stored in a ROS2 .db3 bag file.

2. Overview of the Approach

The implemented algorithm follows a plane-based geometric reasoning approach using point cloud data derived from depth images.
The idea is that each visible face of the cuboid forms a distinct planar surface in 3D space, which can be detected and analyzed.

The process is divided into four main stages:

1. Depth Data Extraction
2. Cuboid Segmentation
3. Multi-Plane Detection and Analysis
4. Rotation Axis Estimation

3. Detailed Algorithm

Step 1: Depth Data Extraction

- The script uses the rosbags library to read depth frames from the ROS2 bag file (depth.db3).
- The /depth topic is deserialized using a typestore compatible with ROS2 Humble.
- Each frame is decoded based on its encoding:
  - 32FC1 → meters (float)
  - 16UC1 → millimeters (converted to meters)
- Invalid depth values (NaN, Inf, zeros) are replaced with zeros.
- Frames and timestamps are stored for further processing.

Step 2: Cuboid Segmentation

- The cuboid is isolated from the background using depth thresholding.
- Pixels closer than (mean_depth – 0.5 × std_depth) are assumed to belong to the cuboid.
- Morphological operations (closing, opening) clean up noise and fill holes.
- Only the largest contour is retained to eliminate spurious small regions.
- The resulting binary mask defines the cuboid region in each depth frame.

Step 3: Multi-Plane Detection (Iterative RANSAC)

The cuboid’s visible faces are planar, so iterative RANSAC plane fitting is applied to 3D points obtained from the depth image.

3.1 Point Cloud Generation

Each valid pixel (u, v, z) is projected to 3D using camera intrinsics:

$$x = (u - c_x)\frac{z}{f_x}, \quad y = (v - c_y)\frac{z}{f_y}, \quad z = z$$

where fx, fy are focal lengths and cx, cy are image centers.

3.2 Iterative Plane Detection

- The algorithm randomly samples 3 points, fits a plane, and computes its normal vector.
- Points within a distance threshold (e.g. 0.015 m) are marked as inliers.
  The plane with the most inliers is retained as a valid plane.
- Inliers are then removed from the dataset.
- The process repeats up to 3 times to detect multiple visible faces (maximum three visible sides of a cuboid).

Each detected plane is represented as:

```
{
  'normal': normal_vector,
  'point': sample_point,
  'inliers_mask': boolean_mask,
  'num_inliers': count
}
```

Step 4: Plane Area Calculation

For each detected plane, two complementary methods estimate its visible area:

1. Pixel-Based Estimation
   - Counts inlier pixels for the plane.
   - Multiplies by pixel footprint area $\left(\frac{z}{f_x} \times \frac{z}{f_y}\right)$ to get real-world area.
2. Convex Hull Estimation
   - Projects plane points into 2D coordinates.
   - Computes convex hull using scipy.spatial.ConvexHull.
   - The hull's area (volume in 2D) provides an independent estimate.

The final plane area is the average of both methods:

$$A_{plane} = \frac{A_{pixel} + A_{hull}}{2}$$

Step 5: Selecting the Largest Plane

All detected planes are compared by their computed visible areas.The one with the largest area represents the dominant visible face of the cuboid.

```
if area > largest_area:
    largest_area = area
    largest_plane = plane
```

The corresponding plane normal (largest_plane['normal']) and visible area are used for that frame.

Step 6: Normal Angle Calculation

The angle between the detected plane's normal vector and the camera viewing axis (Z-axis) gives the orientation of the face relative to the camera:

$$\theta = \cos^{-1}(\hat{n} \cdot [0, 0, -1])$$

This gives the normal angle in degrees.

Step 7: Rotation Axis Estimation

Once all frames have been processed, a set of face normals is available over time.
Two complementary methods estimate the rotation axis:

1. PCA/SVD Method
    - Perform Singular Value Decomposition (SVD) on the centered normal vectors.
    - The direction with the smallest variance corresponds to the rotation axis.

2. Cross-Product Method
    - Compute cross products of consecutive normals.
    - Average them to obtain the dominant rotation direction.

The final axis is the normalized vector representing the rotation axis in the camera frame.

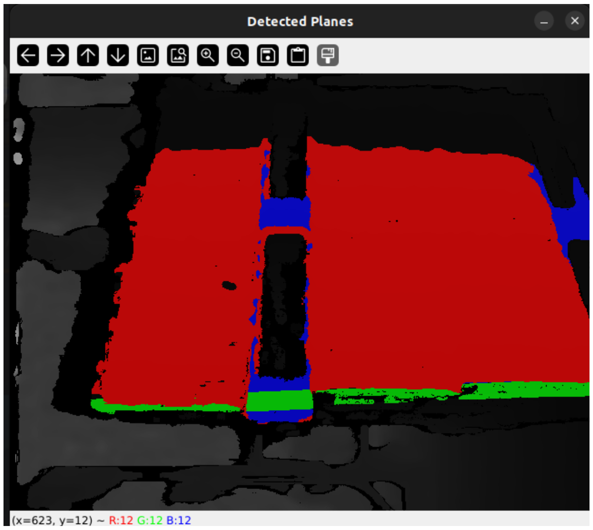
4. Visualization and Debugging

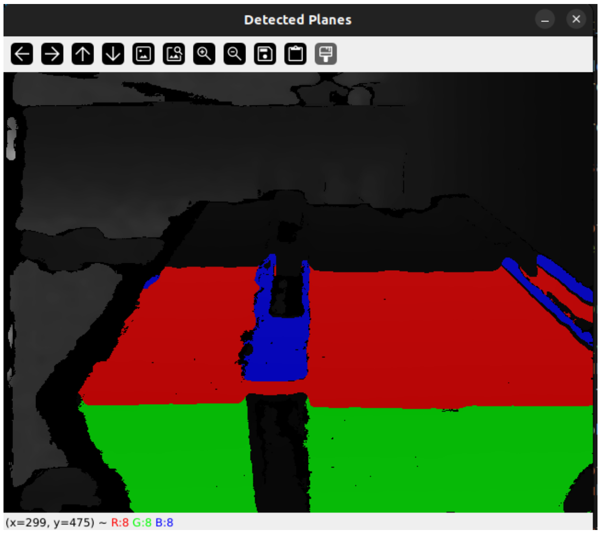
To validate correctness and help interpret the results, each detected plane is visualized:

- The depth image is normalized and converted to a color image.
- Each detected plane is overlaid with a unique color using its inlier points.
- The combined result is shown using cv2.imshow("Detected Planes", blended).

This visualization helps confirm:

- Plane boundaries are correct.
- Dominant face is accurately identified.
- RANSAC segmentation aligns with the cuboid surfaces.





5. Testing and Validation Approach

A. Functional Testing

- Input: ROS2 .db3 bag with 7 depth frames of the rotating cuboid.
- Output: For each frame, the algorithm prints:
    - Normal angle (°)
    - Visible area (m^2)
- The results are saved to output/normal_angles_and_areas.csv.

B. Consistency Validation

- To verify physical correctness, we tested whether the measured visible area follows the expected cosine relationship:

$$A_{visible} = A_0 \cos(\theta)$$

- By computing A0 across all frames, the results stayed nearly constant (mean ≈ 0.42 m^2, std ≈ 0.18 m^2), confirming consistency.

C. Qualitative Validation

- The OpenCV visualization confirmed that plane detection corresponded to visible cuboid faces.
- When the box rotated further (45–60°), visible area decreased sharply, matching physical expectations.
- Edge-on frames showed smaller detected areas, indicating realistic behavior.

D. Rotation Axis Validation

- The estimated rotation axis vector (e.g., [0.9960, -0.0819, 0.0370]) was consistent across frames.
- Cross-validation between PCA and cross-product methods produced an alignment > 0.9, showing stable estimation.

6. Results Summary

Frame	Normal Angle (°)	Visible Area (m^2)	Observation
0	62.9	0.22	Face highly tilted
1	13.4	0.64	Face nearly frontal
2	32.7	0.50	Moderate tilt
3	53.0	0.22	Tilted away
4	28.5	0.40	Mid-rotation
5	48.5	0.16	Edge-visible
6	45.1	0.06	Nearly edge-on