Quantifying Uncertainty of Segmentation of Computed Tomography

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Abstract

Image processing and analysis have become crucial in various fields, including materials science, manufacturing, and non-destructive testing. Computed tomography (CT) scans provide valuable insights into the physical characteristics of objects and materials. Segmentation, the process of identifying different areas of an image and their boundaries, is an essential step in extracting meaningful information from CT scans. However, the reliability and effectiveness of CT scans heavily depend on accurate segmentation. This paper presents a research project conducted in partnership with Pacific Northwest National Laboratory (PNNL) and Embry-Riddle Aeronautical University. The project aims to quantify the uncertainty in edge detection methods applied to CT scans of machined objects, with the ultimate goal of improving the robustness and productivity of material studies in industrial applications.

Provided Data

- The CT data for the test object was provided in the form of 176 tif files.
- Each tif file is a single 150 x 150 image.
- The tif files can be stacked to get 150 x 150 x 176 voxel matrix of data for the test object.
- Values for these voxels generally fall in the range of 9900 to 10600 with higher numbers indicating higher densities.

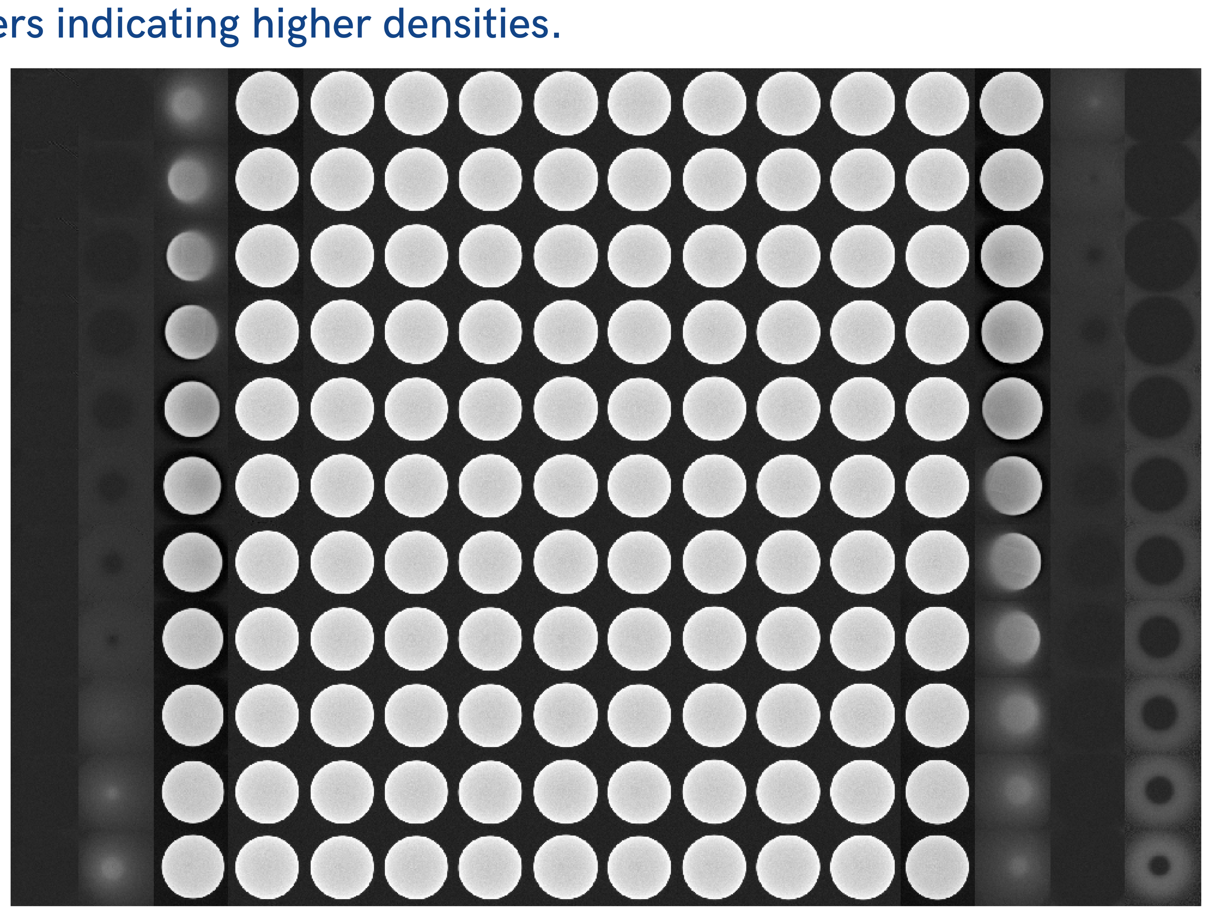

Figure 1. Image of 176 tif files of the test object provided by PNNL.

Methodology

Gradient-based Algorithms:

- Largest pixel intensity gradient change and direction changes are identified, then classified as edges.
- Sobel, Prewitt, Scharr, Robert's Cross

Gaussian-based Algorithms:

- Classifies edges through non-maximum suppression, double thresholding and tracks them using hysteresis.
- Canny

Thresholding:

- Pixels are classified as either edge pixels or non-edge pixels based on a certain threshold value.

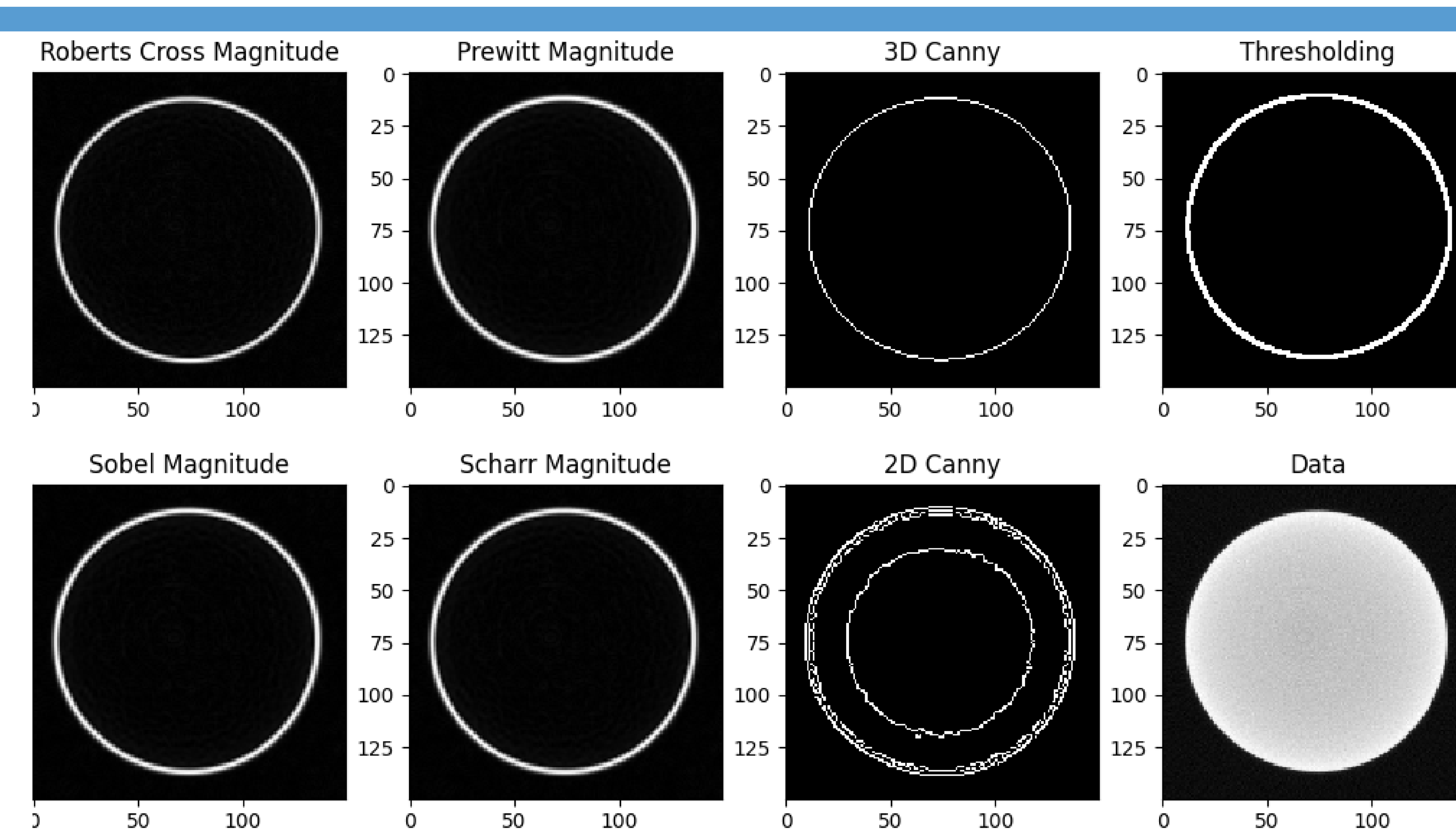

Figure 2. Edge detection algorithm outputs

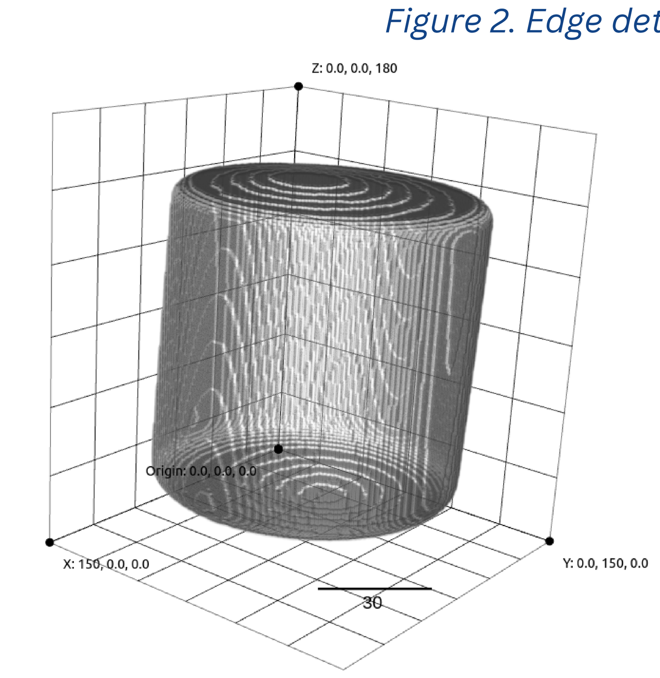

Figure 3. 3D canny output

To determine the optimal edge detection method, we utilize evaluation metrics:

- Jaccard's Index
  - Gauges similarity of two sets
  - Performs an "intersection over union"
  - Ouputs similarity coefficent between 0 and 1

Thresholding Uncertainty:

- Voxels close to boundary may not actually fall cleanly into "object" or "air".
- Identify these voxels by identifying thresholds for "object" and "air.

Local Uncertainty:

- A moving average or locally weighted average can be used along with thresholding to segment the image
- Areas with significant spread in values are harder to predict with this method

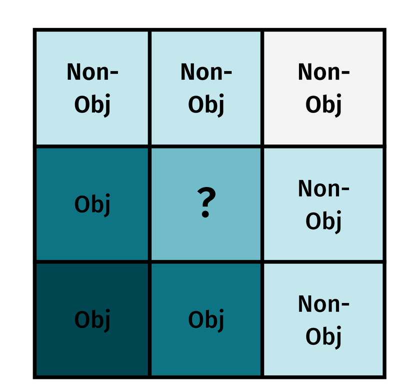

Figure 4. Example of possible local voxels values

Mean and Standard Deviation of Boundary Pixels:

- Select left-most edge detected pixel and determine its location.
- Iterate over edge-detected outputs and locate each pixel representing the left-most edge in every image.
- Calculate the mean and standard deviation of pixel location across the data.

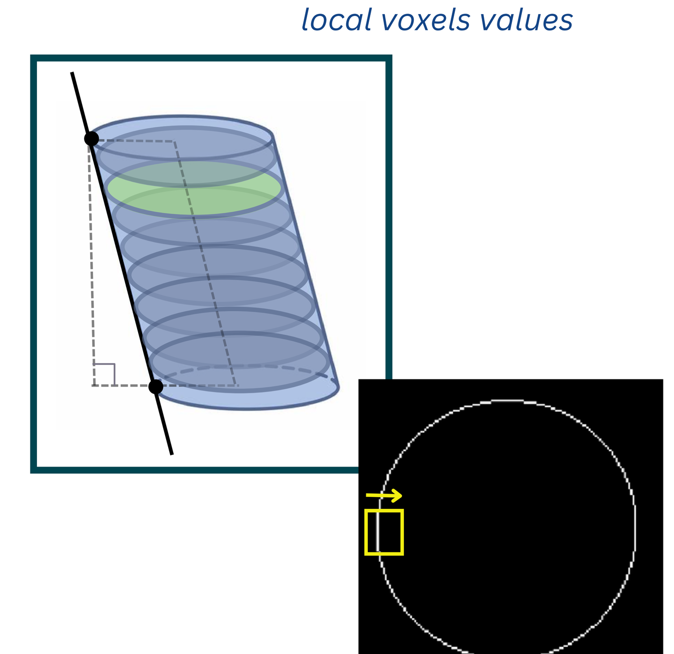

Figure 5. Image depicting "left-most" pixels used to determine mean and standard deviation.

Results

Jaccard Score		
Reference & Canny Control	Reference & Canny	Reference & Sobel
0.89	0.87	0.89
Reference & Prewitt	Reference & Robert's Cross	Reference & Scharr
0.89	0.89	0.89

Figure 6. Table of similarity scores using Jaccard's Index

Scores are within a similar range, indicating the algorithms perform similarly.

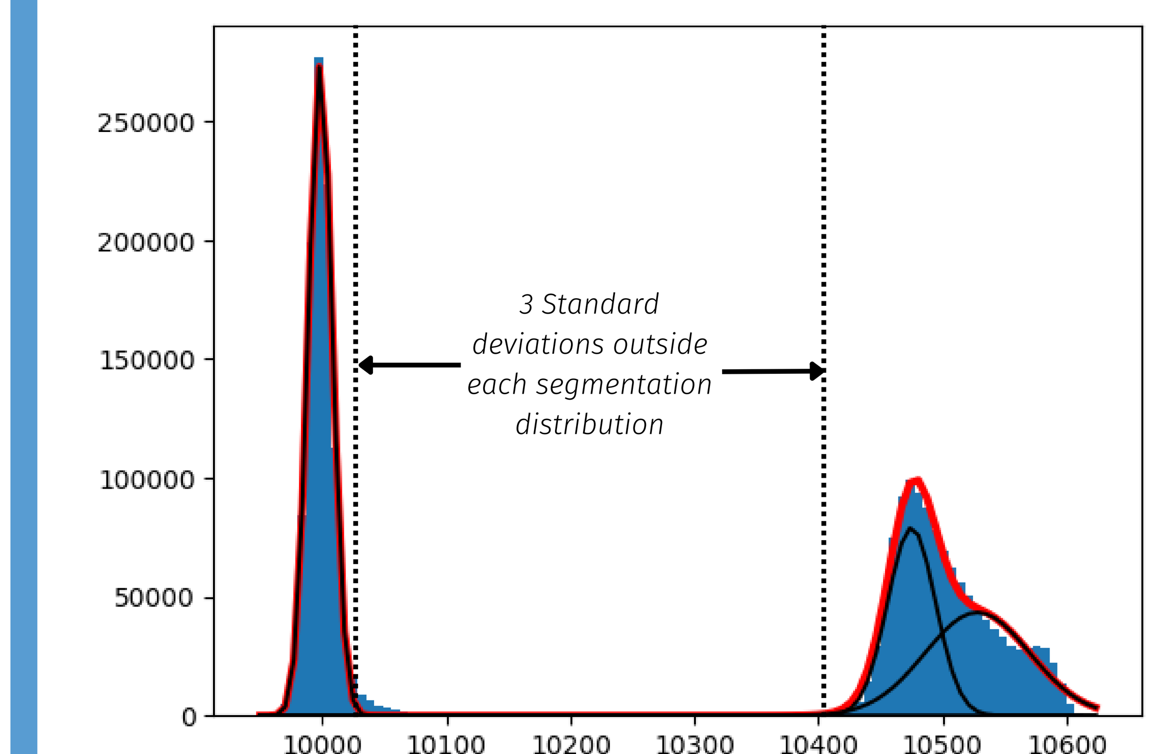

Figure 7. Distribution of voxel intensity values for cropped volume.

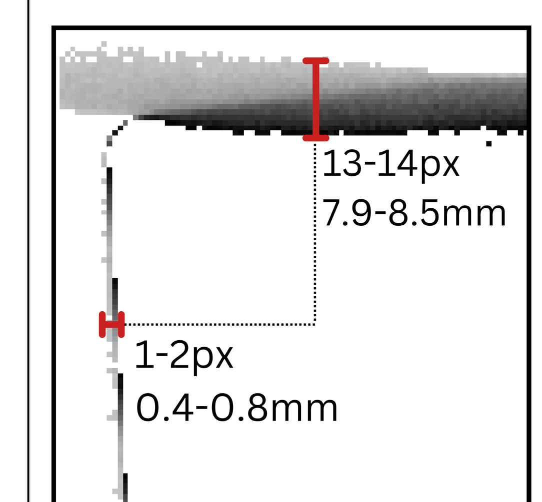

Figure 8. Side view of voxels that are not classified as "object" or "air".

Computed approximate error bars based off of threshold values determined in *Figure 7*. Due to the large gradient at the top of the object, it is harder to classify an edge. This results in a larger error bar compared to the lateral edge.

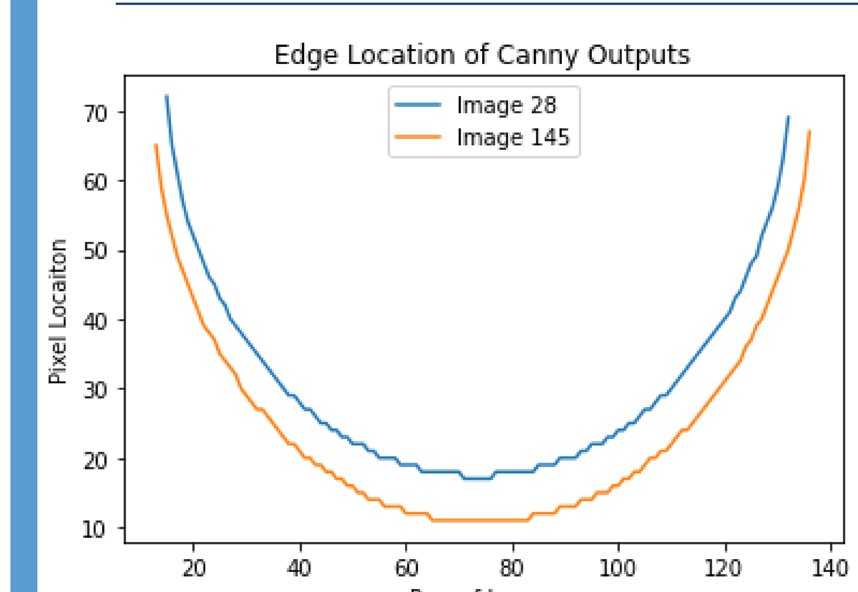

Figure 9. Plot displaying the displacement of the leftmost edge pixel changing over each Canny output image.

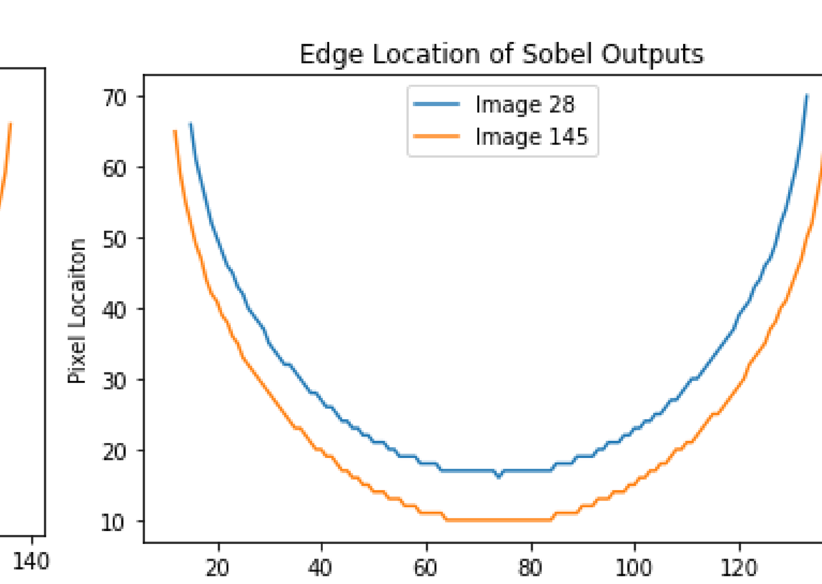

Figure 10. Plot displaying the displacement of the leftmost edge pixel changing over each Sobel output image.

Mean Location (Pixels)	Standard Deviation (Pixels)	Standard Deviation (mm)
(74, 11.58)	1.94	0.79

Figure 11. Table of computed mean and standard deviation for "leftmost" pixel from images 28 - 147.

Indicates tilt displaces boundaries by at most 8 voxels. Standard deviation gives error bar as a result of systematic error in CT scanning process.

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