Assignment 1: Connected Component Labeling and Analysis

Your Name

UGA ID: 81XXXXXXX

CSCI 8820: Computer Vision and Pattern Recognition

Department of Computer Science, University of Georgia

February 12, 2026

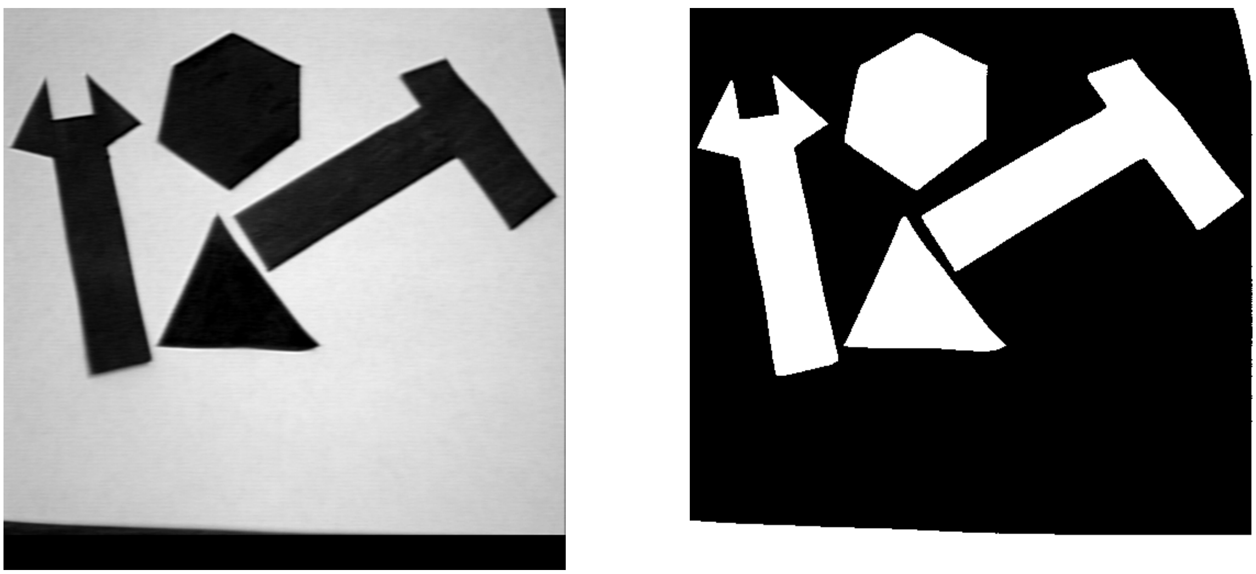
Contents

Introduction and Preprocessing

This report presents the implementation of an iterative Connected Component Labeling (CCL) algorithm to analyze a grayscale image. The objective is to segment objects from the background, extract geometric features, and analyze the impact of size filtering on object detection.

Thresholding and Binary Mask Generation

The input image (B) was converted to a binary image (B_T) using a threshold value of $T = 128$. To ensure the objects of interest were labeled as foreground (1), the algorithm automatically checked the pixel distribution; if the foreground pixels exceeded 50% of the image area, the binary mask was inverted.



(a) Original Grayscale Image (B)

(b) Thresholded Binary Image (B_T)

Figure 1: Preprocessing results showing the conversion from grayscale to binary mask.

Methodology and Mathematical Formulation

Connected Component Labeling (CCL)

An iterative 4-connected CCL algorithm was implemented. The process involved two passes:

1. **First Pass:** The image was raster-scanned. Temporary labels were assigned to foreground pixels based on their top and left neighbors. Label equivalences (collisions) were recorded in a union-find structure.

2. **Second Pass:** Equivalences were resolved to merge connected components, and a final re-labeling step normalized the IDs to sequential integers (1, 2, 3...) for clarity.

Feature Extraction Formulation

For each labeled component, geometric properties were derived using zeroth, first, and second-order moments.

Area and Centroid

The area A is defined as the total number of pixels in the component. The centroid (x_c, y_c) is calculated as:

$$x_c = \frac{1}{A} \sum_{i,j \in R} j, \quad y_c = \frac{1}{A} \sum_{i,j \in R} i \tag{1}$$

where j corresponds to the column index (x-coordinate) and i corresponds to the row index (y-coordinate).

Central Moments

To determine orientation, coordinates were normalized relative to the centroid:

$$x' = j - x_c, \quad y' = i - y_c \tag{2}$$

The second-order central moments a, b, and c were computed as:

$$a = \sum (x')^2 \tag{3}$$

$$b = 2 \sum (x'y') \tag{4}$$

$$c = \sum (y')^2 \tag{5}$$

Orientation and Principal Axes

The orientation θ of the axis of elongation (the axis of least inertia) is given by:

$$\theta = \frac{1}{2} \arctan\left(\frac{b}{a-c}\right) \tag{6}$$

The principal moments of inertia, I_{max} and I_{min}, representing the major and minor axes variances, are:

$$I_{max}, I_{min} = \frac{(a+c) \pm \sqrt{(a-c)^2 + b^2}}{2} \tag{7}$$

Eccentricity

Eccentricity was calculated to classify the shapes (Compact vs. Elongated):

$$\text{Eccentricity} = \sqrt{1 - \frac{I_{min}}{I_{max}}} \tag{8}$$

Experimental Results

The algorithm was tested with three minimum size thresholds: 100, 500, and 1000 pixels. The results below illustrate the trade-off between noise reduction and structural detail.

Case 1: Minimum Size Threshold = 100

At this low threshold, the algorithm captures nearly all potential objects but also retains significant noise.

Figure 2: Labeled Components ($Size \geq 100$). Overlays show Centroids, Bounding Boxes, and Principal Axes.

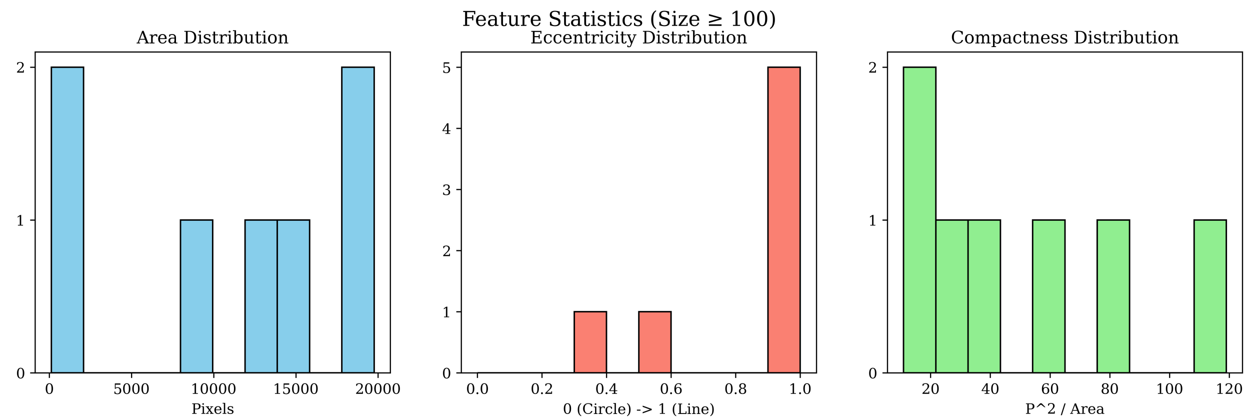


Figure 3: Feature distribution for size threshold 100.

Component Description Table (Size ≥ 100)

ID	Area	Centroid	Bounding Box	Orientation(deg)	Eccentricity	Perimeter	Compactness
1	620	(506.4, 28.2)	[495,0,511,114]	84.7	0.991	196	61.96
2	13148	(207.3, 91.7)	[141,23,270,165]	-49.4	0.388	380	10.98
3	19762	(361.1, 146.6)	[211,46,503,239]	-19.6	0.905	693	24.30
4	15327	(81.3, 196.6)	[7,61,134,334]	79.0	0.963	732	34.96
5	119	(511.0, 175.0)	[511,116,511,234]	90.0	1.000	119	119.00
6	8913	(207.2, 269.8)	[140,190,287,312]	34.8	0.573	383	16.46
7	18472	(241.1, 493.0)	[0,377,511,511]	0.5	0.997	1200	77.96

Figure 4: Extracted Features for Size $\geq$ 100.

Case 2: Minimum Size Threshold = 500

Increasing the threshold eliminates small artifacts, leaving distinct, meaningful components.

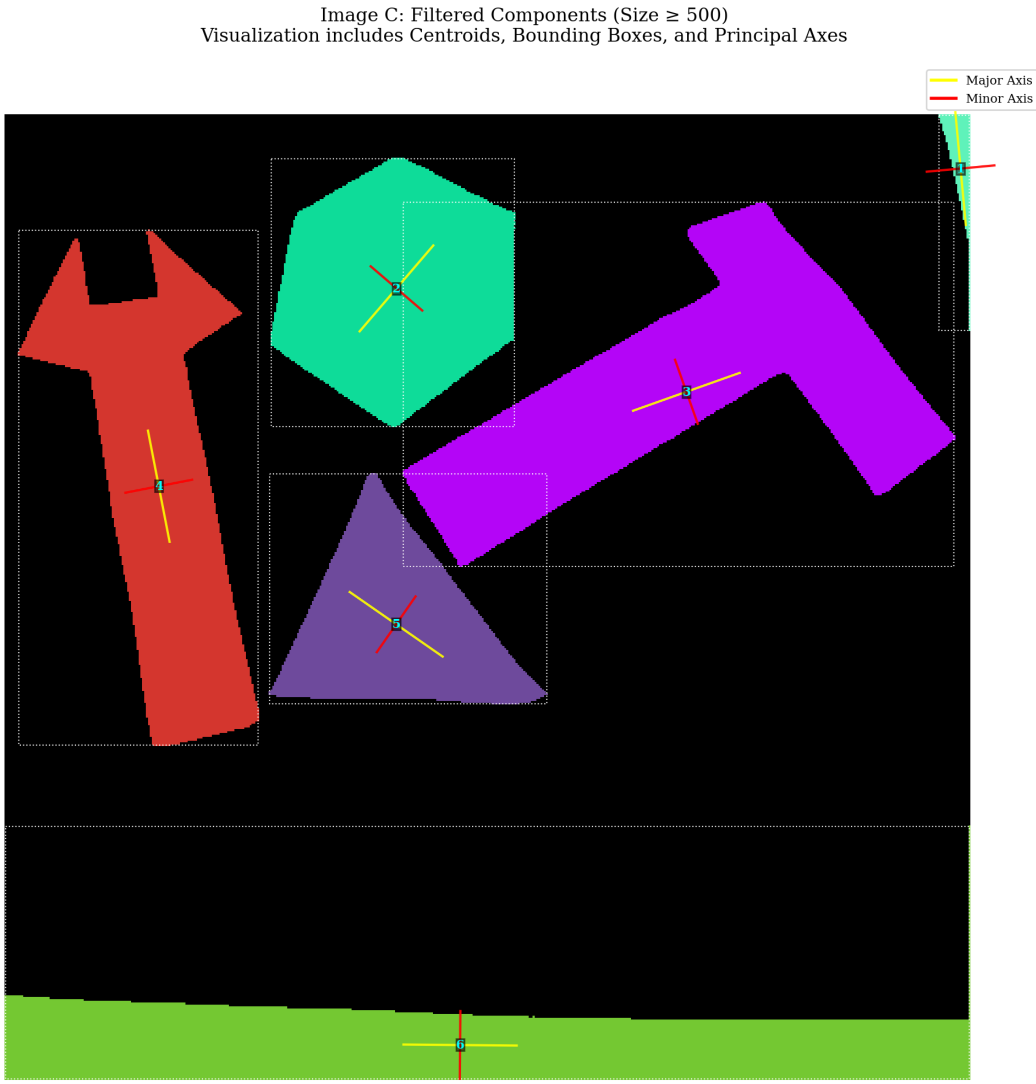


Figure 5: Labeled Components (*Size* $\geq$ 500). The principal axes (Yellow=Major, Red=Minor) confirm the orientation calculations.

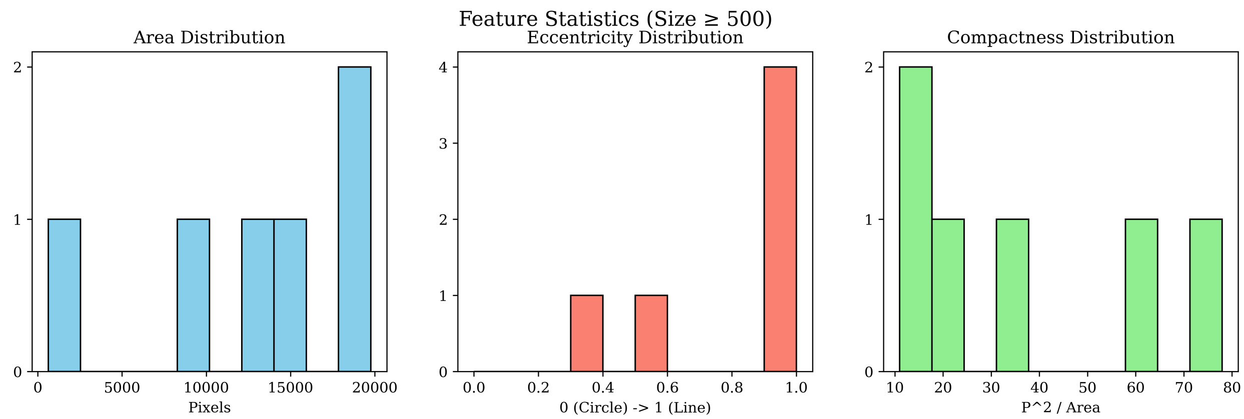


Figure 6: Feature distribution for size threshold 500.

Component Description Table (Size ≥ 500)

ID	Area	Centroid	Bounding Box	Orientation(deg)	Eccentricity	Perimeter	Compactness
1	620	(506.4, 28.2)	[495,0,511,114]	84.7	0.991	196	61.96
2	13148	(207.3, 91.7)	[141,23,270,165]	-49.4	0.388	380	10.98
3	19762	(361.1, 146.6)	[211,46,503,239]	-19.6	0.905	693	24.30
4	15327	(81.3, 196.6)	[7,61,134,334]	79.0	0.963	732	34.96
5	8913	(207.2, 269.8)	[140,190,287,312]	34.8	0.573	383	16.46
6	18472	(241.1, 493.0)	[0,377,511,511]	0.5	0.997	1200	77.96

Figure 7: Extracted Features for Size $\geq$ 500.

Case 3: Minimum Size Threshold = 1000

At the highest threshold, only the largest primary objects remain.

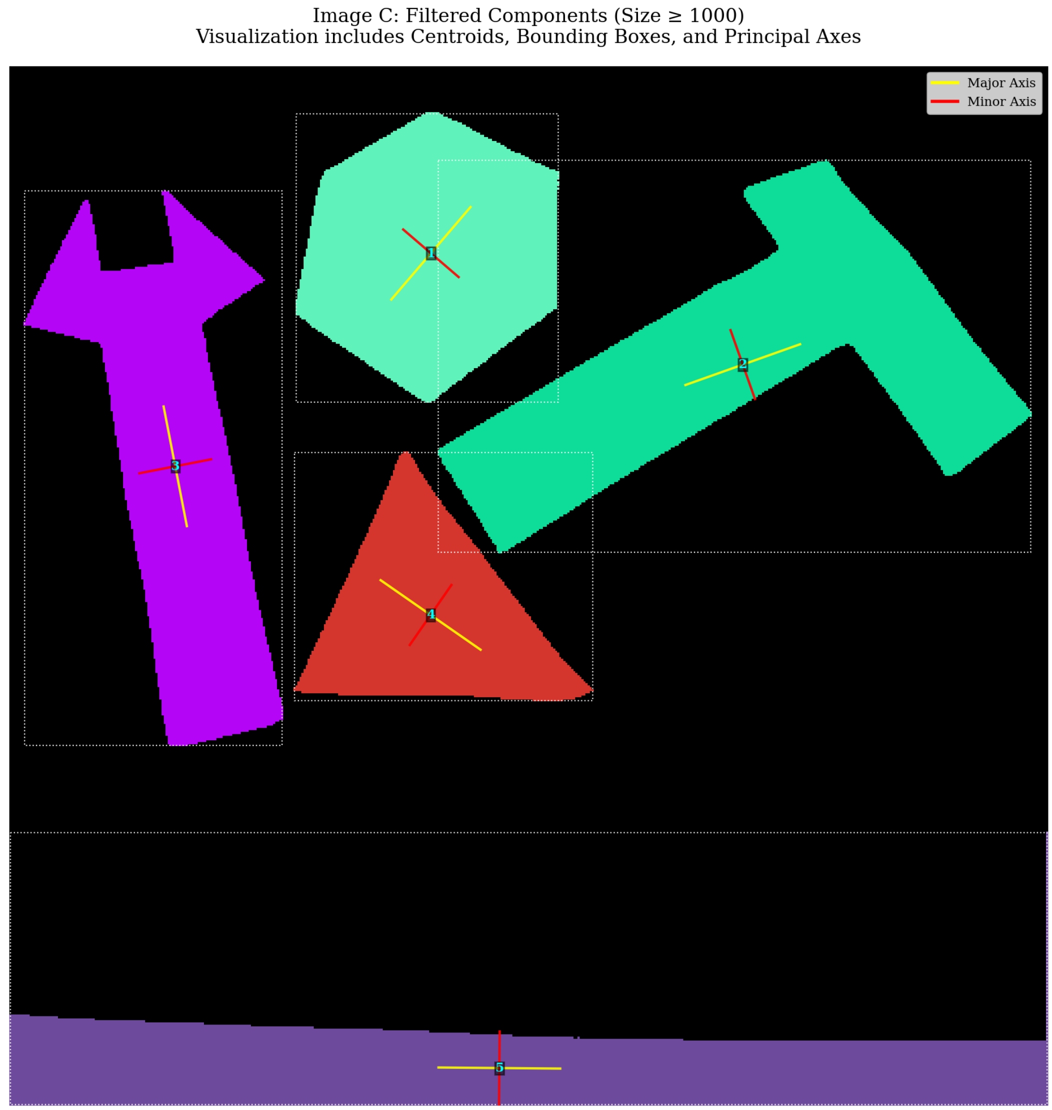


Figure 8: Labeled Components (*Size* $\geq$ 1000).

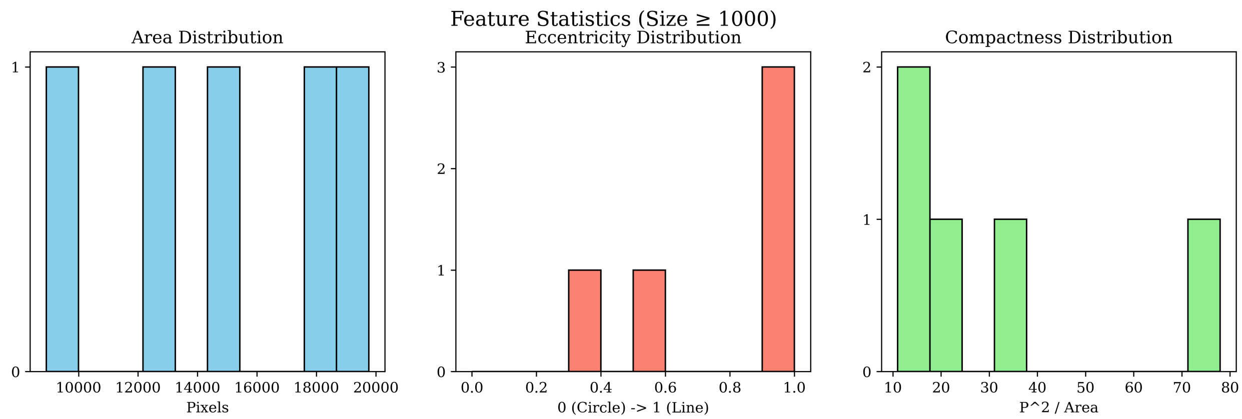


Figure 9: Feature distribution for size threshold 1000.

Component Description Table (Size ≥ 1000)

ID	Area	Centroid	Bounding Box	Orientation(deg)	Eccentricity	Perimeter	Compactness
1	13148	(207.3, 91.7)	[141,23,270,165]	-49.4	0.388	380	10.98
2	19762	(361.1, 146.6)	[211,46,503,239]	-19.6	0.905	693	24.30
3	15327	(81.3, 196.6)	[7,61,134,334]	79.0	0.963	732	34.96
4	8913	(207.2, 269.8)	[140,190,287,312]	34.8	0.573	383	16.46
5	18472	(241.1, 493.0)	[0,377,511,511]	0.5	0.997	1200	77.96

Figure 10: Extracted Features for Size $\geq$ 1000.

Discussion and Analysis

Noise Analysis and Size Filter Trade-off

As the minimum size specification increases, smaller components are progressively suppressed.

- At **T=100**, the system detects fine details but includes granular noise (likely artifacts from thresholding).
- At **T=1000**, the system acts as a high-pass spatial filter, retaining only the dominant structures.

This demonstrates a clear trade-off: lower thresholds provide high recall of potential features but low precision due to noise, whereas higher thresholds ensure high precision for large objects at the cost of missing finer details.

Geometric Validation

To verify the correctness of the moment calculations, the property $I_{max} + I_{min} = a + c$ was checked for every component. The error was consistently near machine epsilon ($< 10^{-14}$), confirming that the principal axes visualization (Yellow/Red lines) correctly represents the true mass distribution of the components.

Conclusion

The iterative CCL algorithm successfully segmented the input image. The feature extraction pipeline provided robust geometric descriptors, and the visual overlay of principal axes confirmed the accuracy of the moment-based orientation calculations.

Appendix: Source Code

(Attach your Python code hardcopy here if required, or submit as separate file.)