

Assignment 1: Connected Component Labeling and Analysis

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1 Introduction and Preprocessing

This report implements an iterative Connected Component Labeling (CCL) algorithm to segment and analyze objects in a grayscale image. The pipeline involves binary thresholding, labeling, and geometric feature extraction.

1.1 Thresholding and Binary Mask Generation

The input image B was converted to a binary image B_T using a fixed threshold $T = 128$. To ensure consistency, the mask was automatically inverted by $B_T = 1 - B_T$.

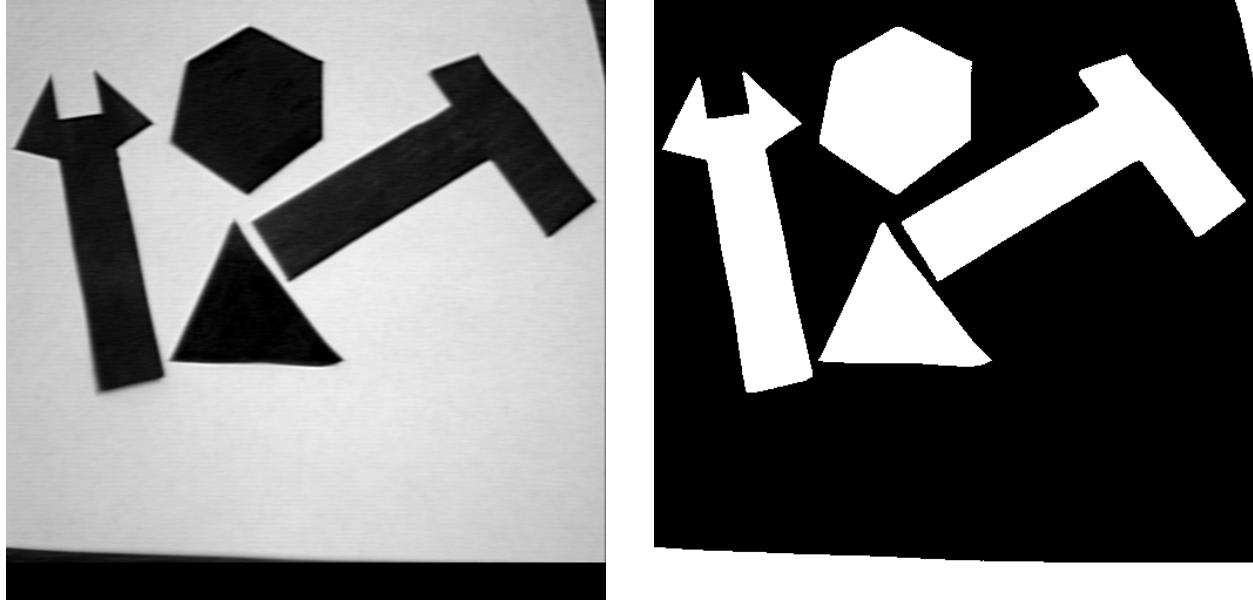


Figure 1: Preprocessing: Conversion from 8-bit grayscale to binary mask.

2 Methodology

2.1 Connected Component Labeling (CCL)

An iterative 4-connected CCL algorithm was implemented using a two-pass approach:

1. **First Pass:** Raster-scanning the image and assigning temporary labels based on the 4 connectivity of the top and left neighbors. Collisions were managed via a union-find data structure.
2. **Second Pass:** Resolution of equivalences to merge components and sequential re-labeling of the final IDs.

2.2 Feature Extraction and Mathematical Models

Geometric properties were derived from the zeroth-, first-, and second-order central moments.

- **Area and Centroid:** The area and centroid coordinates of a binary object $B(i, j)$ are defined as

$$A = \sum_{i=1}^n \sum_{j=1}^m B(i,j), \quad (1)$$

$$X_c = \frac{1}{A} \sum_{i=1}^n \sum_{j=1}^m j B(i,j), \quad (2)$$

$$Y_c = \frac{1}{A} \sum_{i=1}^n \sum_{j=1}^m i B(i,j), \quad (3)$$

where A denotes the object area, and (X_c, Y_c) represents the centroid location.

- **Orientation (θ):** The principal axis orientation is obtained by minimizing the second central moment:

$$\theta = \frac{1}{2} \tan^{-1} \left(\frac{b}{a - c} \right), \quad (4)$$

where a , b , and c are second-order central moments.

- **Second-Order Central Moments:** These moments are computed as

$$a = \sum_{i=1}^n \sum_{j=1}^m [X'(i,j)]^2 B(i,j), \quad (5)$$

$$b = 2 \sum_{i=1}^n \sum_{j=1}^m X'(i,j) Y'(i,j) B(i,j), \quad (6)$$

$$c = \sum_{i=1}^n \sum_{j=1}^m [Y'(i,j)]^2 B(i,j), \quad (7)$$

where $X'(i,j) = j - X_c$ and $Y'(i,j) = i - Y_c$ denote centroid-shifted coordinates.

- **Eccentricity:** The eccentricity of the object is computed from the eigenvalues of the covariance matrix:

$$\text{Eccentricity} = \sqrt{1 - \frac{I_{\min}}{I_{\max}}}, \quad (8)$$

where I_{\max} and I_{\min} are the major and minor principal moments, respectively.

Note: Consistency of the moment calculations was verified by checking that the invariant relation $|a + c - (I_{\max} + I_{\min})|$ remained close to zero. With a maximum absolute error of 6.0×10^{-8} across all tests.

- **Compactness:** Compactness, a measure of shape circularity, is defined as

$$\text{Compactness} = \frac{P^2}{A}, \quad (9)$$

where P is the perimeter and A is the area.

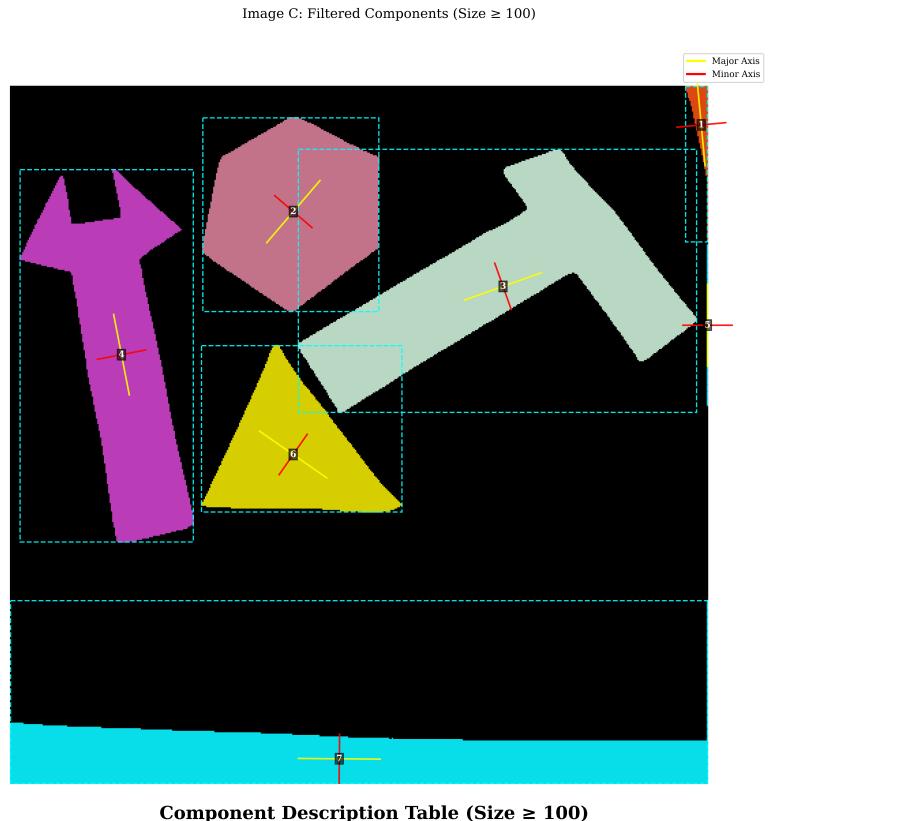
3 Experimental Results

The algorithm was evaluated across three minimum size thresholds: 100, 500, and 1000 pixels.

Note: Kindly correlate the Labeled Components with their respective Feature Tables: For Case 1 refer to Figure 2, and for Case 2 (Figure 3) and Case 3 (Figure 5) refer to Figure 4 and Figure 6 respectively.

3.1 Case 1: Minimum Size Threshold = 100

At $T_{size} = 100$, the algorithm labels artifacts/noise in the image as components along with primary objects of interest as shown in Figure 2.



Total Components Labelled:	7
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Figure 2: Labeled Components and Corresponding Feature Table for Case 1

3.2 Case 2: Minimum Size Threshold = 500

Increasing the threshold effectively filters out noise while correctly labelling the primary objects.

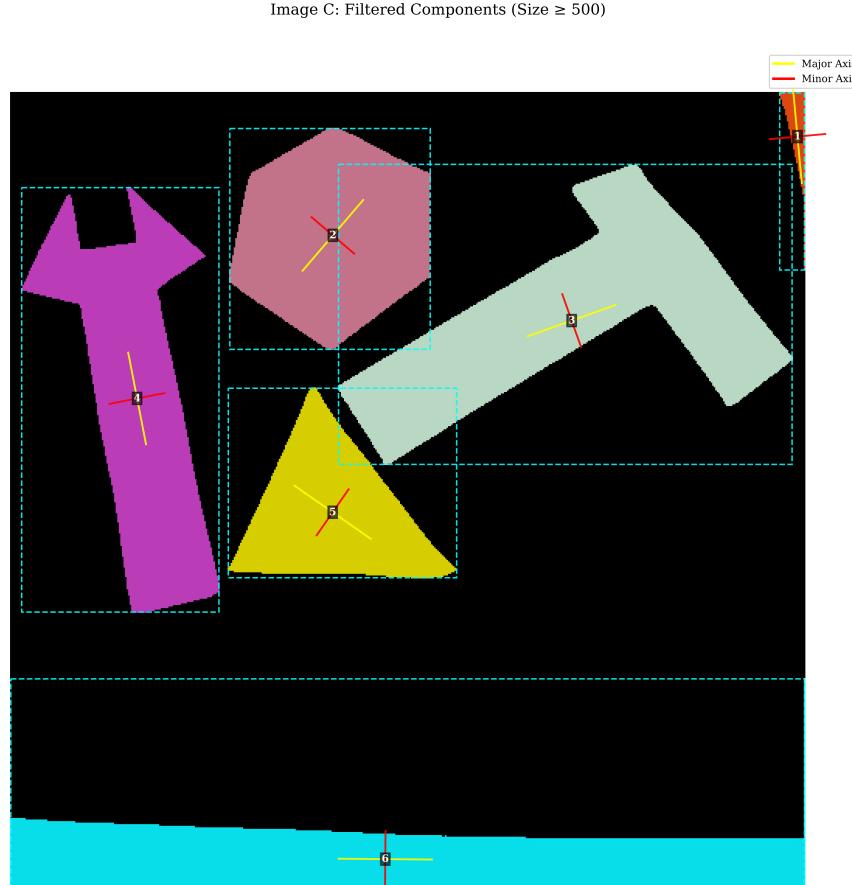


Figure 3: Labeled Components ($Size \geq 500$).

Component Description Table (Size ≥ 500)

ID	Area	Centroid	Bounding Box	Orient(deg)	Elongation	Eccentricity	Perimeter	Compactness
1	620	(506.4, 28.2)	[495,0,511,114]	84.7	57.10	0.991	196	61.96
2	13148	(207.3, 91.7)	[141,23,270,165]	-49.4	1.18	0.388	380	10.98
3	19762	(361.1, 146.6)	[211,46,503,239]	-19.6	5.54	0.905	693	24.30
4	15327	(81.3, 196.6)	[7,61,134,334]	79.0	13.80	0.963	732	34.96
5	8913	(207.2, 269.8)	[140,190,287,312]	34.8	1.49	0.573	383	16.46
6	18472	(241.1, 493.0)	[0,377,511,511]	0.5	158.65	0.997	1200	77.96

Total Components Labelled:	6
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Figure 4: Extracted Features for Case 2.

3.3 Case 3: Minimum Size Threshold = 1000

At $T_{size} = 1000$, only the most significant geometric structures remain.

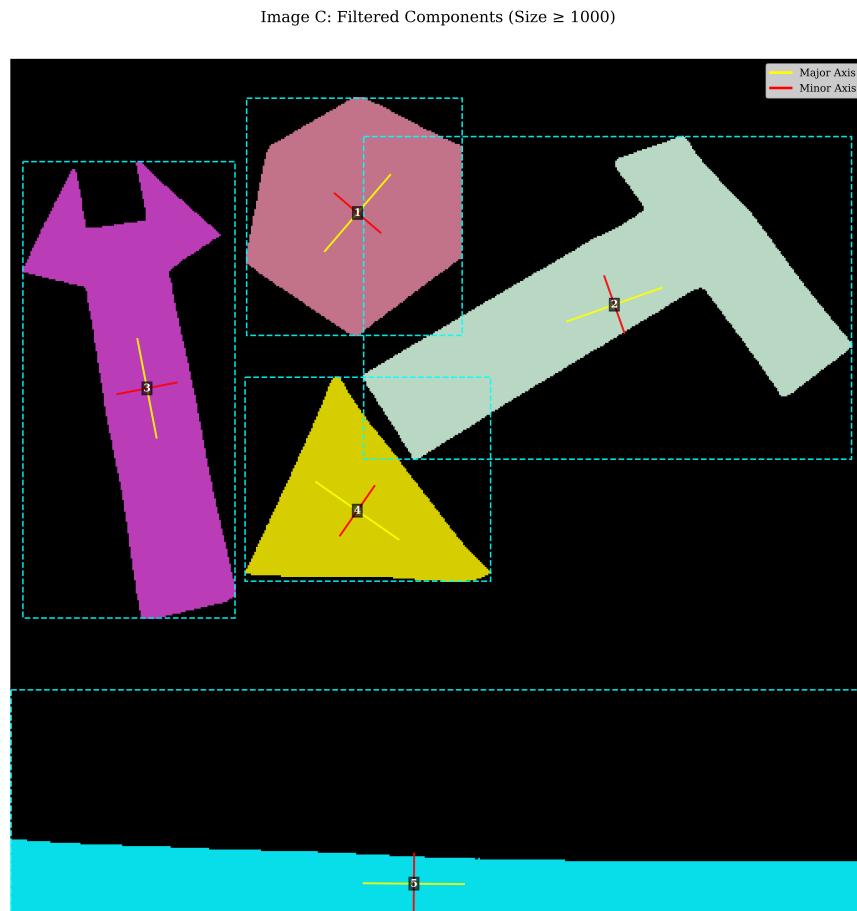


Figure 5: Labeled Components ($Size \geq 1000$).

Component Description Table (Size ≥ 1000)

ID	Area	Centroid	Bounding Box	Orient(deg)	Elongation	Eccentricity	Perimeter	Compactness
1	13148	(207.3, 91.7)	[141,23,270,165]	-49.4	1.18	0.388	380	10.98
2	19762	(361.1, 146.6)	[211,46,503,239]	-19.6	5.54	0.905	693	24.30
3	15327	(81.3, 196.6)	[7,61,134,334]	79.0	13.80	0.963	732	34.96
4	8913	(207.2, 269.8)	[140,190,287,312]	34.8	1.49	0.573	383	16.46
5	18472	(241.1, 493.0)	[0,377,511,511]	0.5	158.65	0.997	1200	77.96

Total Components Labelled:	5
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Figure 6: Extracted Features for Case 3.

4 Analysis

4.1 Component Descriptions

The following components were identified and analyzed based on their geometric properties and attributes:

Hammer: The largest component in the scene with an area of 19,762 pixels. It exhibits an elongation of 5.54 and a distinct orientation of approximately -19.6°.

Wrench: A highly elongated tool-shaped object with an area of 15,327 pixels and a near-vertical orientation of 79.0°.

Hexagon: A compact geometric shape with the lowest eccentricity (0.388) among the primary objects, indicating a more equilateral structure.

Triangle: A mid-sized geometric component with an area of 8,913 pixels and a relatively low elongation of 1.49.

Cyan Base: A wide, horizontal structure spanning the bottom of the frame. It has the highest perimeter (1,200 pixels) and a very high elongation of 158.65 due to its thin, wide aspect ratio.

Orange Sliver (Noise): A thin vertical artifact located at the top-right edge with an area of 620 pixels. It is removed when the size threshold is increased to 1000.

Small Fragment (Noise): A tiny vertical sliver with an area of only 119 pixels, which is immediately filtered out at any threshold above 100.

4.2 Noise Analysis and Size Filter Trade-off

The experimental results highlight a fundamental trade-off:

- **Lower Threshold (100 & 500):** Small noise components are detected as objects.
- **High Threshold (1000):** Fine structural details may be lost if they do not meet the pixel count (T_{size}) requirement.

4.3 Geometric Validation

To ensure the accuracy of the moment-based orientation, the invariant property $I_{max} + I_{min} = a + c$ was calculated. The error was consistently negligible (6.0×10^{-8}), validating the orientation calculation and axis visualization.

5 Conclusion

The iterative CCL algorithm effectively labelled the components in the test image. The 1000-pixel threshold successfully isolates the Wrench, Hammer, Hexagon, Triangle, and Base as the primary structural components

Note: For source code kindly refer to appendix at the end.

Appendix: Source Code

The following Python script was used to perform all operations described in this report.

```
1 # Paste your python code here.  
2 # It will be formatted automatically with syntax highlighting.
```