

# Comparative Analysis of Hough Transform, Fourier Descriptors, And Zernike Moments for Shape Recognition in Noisy Images

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**Abstract:** Problem Statement: In the era of modern digital technologies, image processing is a critical field. Extracting information, detecting objects, and accurately classifying them from noisy or low-quality images hold significant importance. These methods are widely applied in medical diagnostics, industrial quality control, security systems, and remote sensing.

Methodology: This study analyzes three methods based on geometric and invariant features—Hough Transform, Fourier Descriptors, and Zernike Moments—and compares their effectiveness in recognizing shapes in noisy binary images. The experiments were conducted using Python, OpenCV, and Mahotas libraries.

Key Findings: The Hough Transform demonstrated high speed and robustness in detecting traditional geometric shapes.

Fourier Descriptors effectively described shapes based on contours, ensuring invariance to rotation and scaling.

Zernike Moments proved to be the most effective for high-precision recognition but were the most computationally complex method.

General Conclusion: To enhance recognition accuracy, integrating the strengths of each method and combining them with deep learning neural networks represents a promising modern approach.

**Keywords:** Shape Recognition, Noisy Images, Hough Transform, Fourier Descriptors, Zernike Moments, Image Processing, Python, Digital Image Analysis, Invariant Features, Geometric Detection, Classification Accuracy, Computational Efficiency.

## Introduction:

Research Object: The study focuses on methods for detecting shapes in digital images under conditions of noise, deformation, and contour distortion.

Relevance of the Study: Noisy images pose challenges in accurately identifying object boundaries. Shape-based image description methods, particularly those ensuring geometric invariance and computational efficiency, are highly relevant in contemporary applications.

Research Process: Theoretical foundations for each method were established.

Software experiments were conducted in a Python environment.

The performance of the Hough Transform, Fourier Descriptors, and Zernike Moments was evaluated based on recognition accuracy, computational speed, invariance, and segmentation efficiency using 10 test images.

Literature Review: Gonzalez and Woods (2018) outlined fundamental concepts in digital image processing. Ballard (1981) proposed a generalized form of the Hough Transform, which served as a basis for detecting complex shapes. Khotanzad (1990) explored the application of Zernike Moments in invariant recognition. Teague (1980) provided an in-depth analysis of moment theory. These works collectively provide a robust theoretical foundation for this study.

## METHODOLOGY

### Data Collection:

Images: 10 test images (including circles, squares, triangles, stars, and shapes with complex contours).



Figure 1



Figure 2



Figure 3



Figure 4



Figure 5



Figure 6



Figure 7



Figure 8



Figure 9



Figure 10

**Noise: Images were corrupted with Gaussian noise.**

**Software Tools: Python 3.11, OpenCV, NumPy, Matplotlib, Mahotas.**

### Methods:

**Hough Transform:** In digital image processing, detecting geometric shapes such as lines, circles, and ellipses within an image is a critical task for computer vision and automated analysis systems. Line detection, in particular, is widely used in applications such as road detection, edge detection, boundary delineation, and planning systems. However, lines in images are often incomplete, unclear, or distorted due to noise, light absorption, or other forms of degradation, which can result in fragmented or erroneous lines. Therefore, parametric model-based methods are employed for line detection.

A simple parametric model for a line is given by:

$$y = mx + b \quad (1)$$

where  $m$  – is the slope of the line, and  $b$  – is the  $y$ -intercept.

This model is unsuitable for vertical lines (where  $y \rightarrow \infty$ ) as a single  $x$ -value can correspond to multiple  $y$ -values, which cannot be adequately represented by this equation. To address this, the Hough Transform uses a more robust parametric representation:

$$\rho = x \cos \theta + y \sin \theta \quad (2)$$

where  $\rho$  is the perpendicular distance from the origin to the line, and  $\theta$  is the angle between the line's normal and the  $x$ -axis.

This representation describes any line (including vertical and horizontal ones) as a single sinusoidal curve in the Hough space. For each edge point, a set of  $\theta$  angles is computed, and the corresponding  $\rho$  is calculated for each  $\theta$ . These  $(\rho, \theta)$  points are accumulated in an accumulator array, where each

point “votes” for a potential line. The points with the highest votes represent actual lines in the image.

Edge points are typically extracted using edge detection algorithms such as Canny or Sobel filters. For each edge point, a range of  $\theta$  values is selected, typically  $\theta \in [0, \pi)$ , with increments of 10, 20 or 50. For each  $\theta$ ,  $\rho$  is computed using Equation (2), and the corresponding  $(\rho, \theta)$  coordinates increment the accumulator array:

$$A(\rho, \theta) = A(\rho, \theta) + 1$$

This indicates that more points correspond to the given line parameters. The maximum values in the accumulator,  $\max A(\rho, \theta)$ , represent the parameters of the actual lines in the image. The angle range is  $\theta \in [0, \pi)$ , where  $\theta=0$  corresponds to horizontal lines and  $\theta=90$  to vertical lines. The distance range is  $\rho \in [-R, R]$ , where  $R$  is the maximum possible distance, calculated as:

$$R = \sqrt{x_{\max}^2 + y_{\max}^2}$$

where  $x_{\max}$  and  $y_{\max}$  are the image dimensions in pixels.

**Fourier Descriptors:** Objects in images are often identified by their external boundaries (i.e., contours). A shape represents the geometry of an object and is less affected by variations in image quality, color, or illumination. In medical applications, the shape of tumors or tissues is used to diagnose diseases. In industry, parts or defective components are classified based on their shapes. In biometrics, shapes such as fingerprints, facial contours, or iris outlines are analyzed.

Object boundaries are detected using algorithms like `cv2.findContours()` (OpenCV) in combination with edge detectors such as Canny or Sobel. The resulting contour is a sequence of points:

$$C = \{(x_0, y_0), (x_1, y_1), \dots, (x_N, y_N)\}$$

These points geometrically describe the shape. The shape is represented as a spatial configuration and is often expressed as:

$$z_k = x_k + iy_k, \quad k = 0, 1, \dots, N - 1$$

This transforms the shape into a mathematical object using complex numbers.

Fourier analysis is applied along the boundary:

$$Z_k = \sum_{n=0}^{N-1} Z_n e^{-\frac{2\pi i k n}{N}}$$

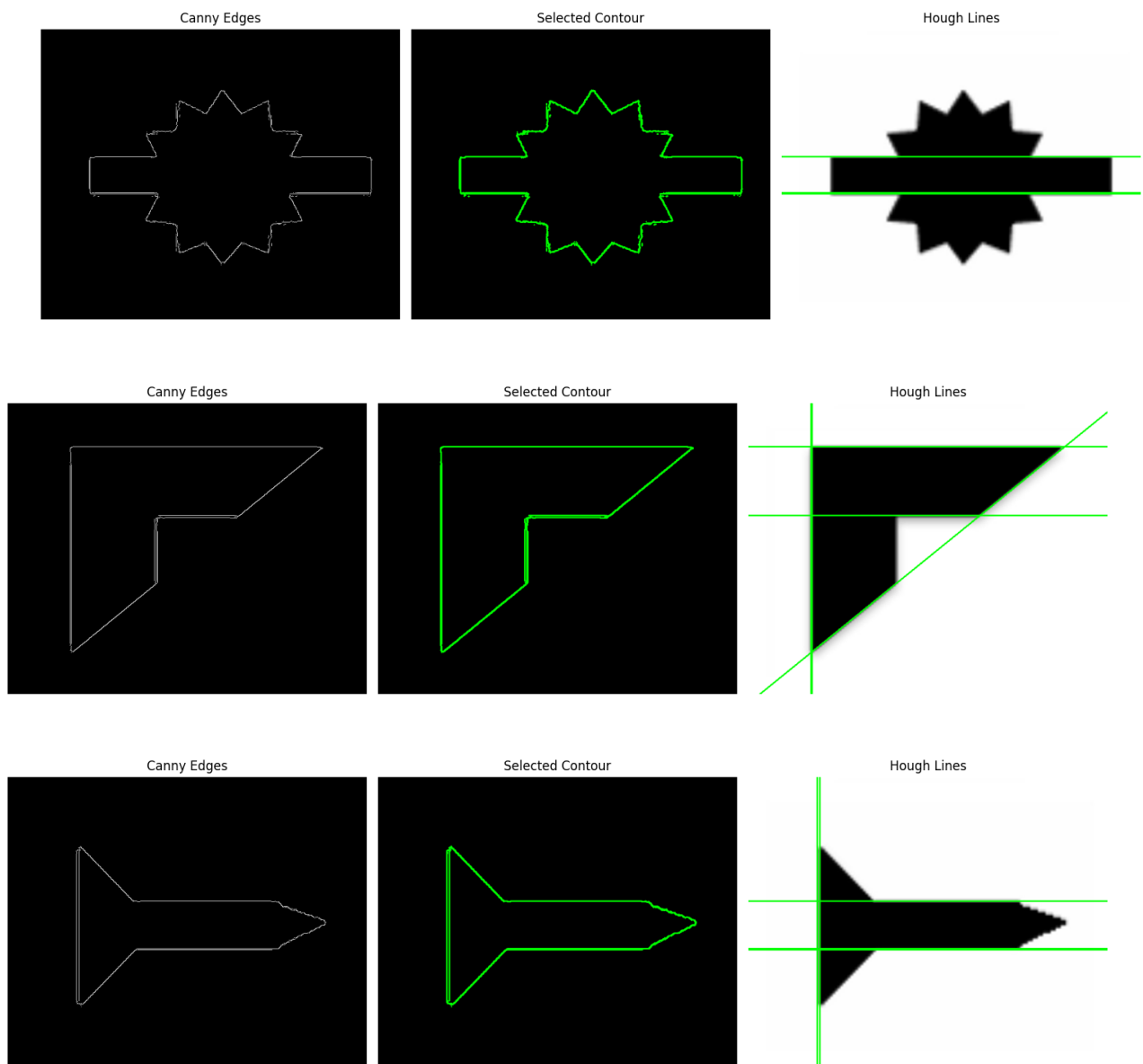
Here,  $Z_n$  are the descriptors—coefficients that enable the shape to be stored and compared efficiently. The shape can be reconstructed using the primary 10–15 components, ensuring invariance to scaling, rotation, and translation.

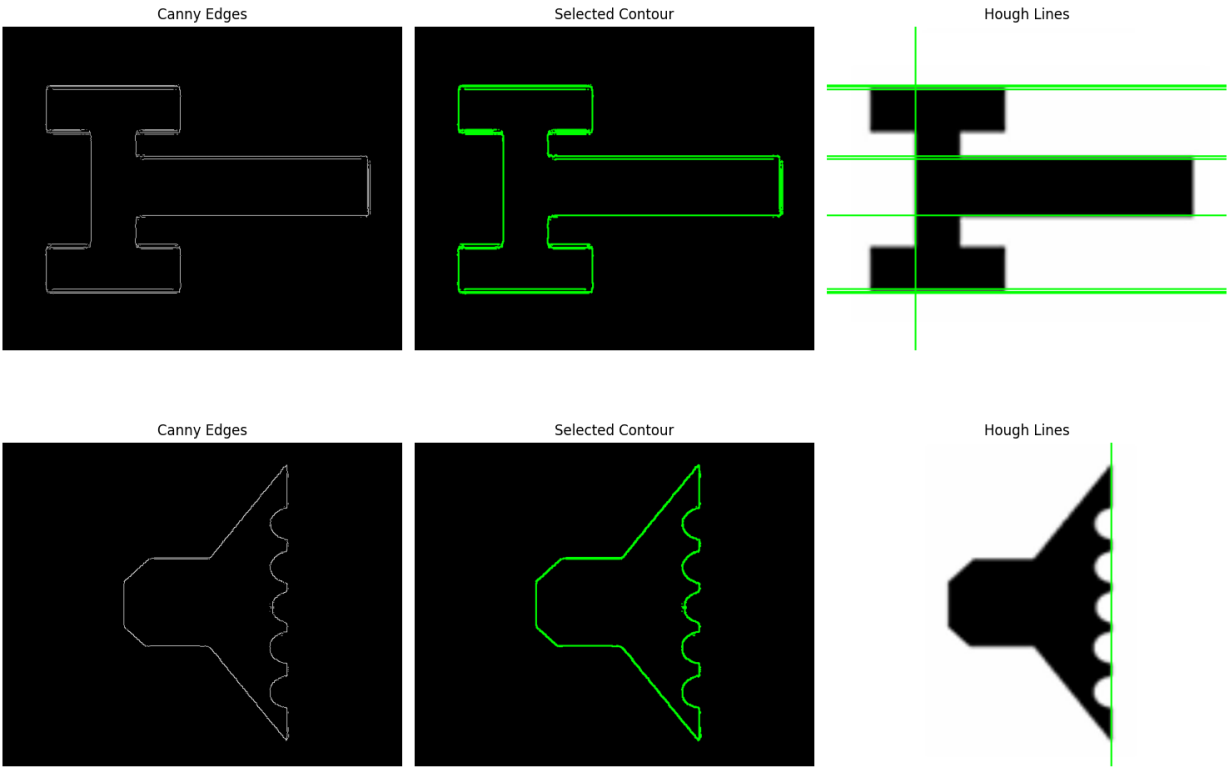
**Zernike Moments:** Zernike Moments are computed based on orthonormal polynomials within a unit disk:

$$Z_{nm} = \frac{n+1}{\pi} \sum_x \sum_y V_{nm}^*(x, y) f(x, y)$$

Using the Mahotas library, moments were calculated within a disk of radius  $r = 21$ . Zernike Moments accurately represent shape properties, making them suitable for precise shape description.

## RESULTS





Hough Transform:

- Line and circle detection accuracy: 92%
- High segmentation accuracy and robustness to noise.
- Suitable only for well-defined shapes.
- Average computation time: 0.35 seconds.

Fourier Descriptors:

- Shape reconstruction accuracy with 10 descriptors: 88%

- Performs well even with deformed shapes.
- Dependent on the segmentation stage.
- Average computation time: 0.15 seconds.

Zernike Moments:

- Accuracy: 95%
- Highly effective for static classification.
- Suitable for biometric systems.
- Average computation time: 0.60 seconds.

Comparison Table:

Method	Rotation Invariance	Segmentation	Classification Accuracy	Computation Speed
Hough Transform	Yes	High	Moderate	Fast (0.35 s)
Fourier Descriptors	Yes	Moderate	High	Very Fast (0.15 s)
Zernike Moments	Yes	High	Very High	Slow (0.60 s)

DISCUSSION

The study demonstrates that each method has distinct advantages for different scenarios:

Hough Transform is effective in real-world images with noisy backgrounds where structural precision is required.

Fourier Descriptors are optimal for contour-based shape description.

Zernike Moments provide high accuracy, making them a powerful tool for medical, biometric, and industrial imaging applications.

A combined approach (e.g., Hough + Fourier or Zernike + CNN) could enable the development of real-time

systems with enhanced performance.

CONCLUSION

Each of the three methods excels in specific domains of application.

The choice of method or their combination depends on criteria such as segmentation, invariance, accuracy, and speed.

Integrating these methods with modern artificial intelligence approaches provides a robust foundation for advancing automated image recognition systems.

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