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SHAPE RECOGNITION IN NOISY IMAGES USING AI ALGORITHMS

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Abstract: This study investigates the application of artificial intelligence (AI) algorithms for robust shape recognition in noisy binary images, addressing challenges in medical imaging (e.g., organ segmentation in MRI scans), industrial inspection (e.g., defect detection in automotive parts), and remote sensing (e.g., object identification in satellite imagery). Three AI-based methods—Hough Transform (HT), Fourier Descriptors (FD), and Zernike Moments (ZM)—were implemented and evaluated using Python-based tools (OpenCV, Mahotas). Experimental results demonstrate that Zernike Moments achieve the highest accuracy (95%) in high-noise conditions, Fourier Descriptors excel in reconstructing complex contours, and Hough Transform is fastest for detecting basic geometric shapes. A hybrid approach integrating these methods with deep learning, such as Convolutional Neural Networks (CNNs), is proposed to enhance accuracy and scalability.

Keywords: Shape Recognition, Noisy Images, Hough Transform, Fourier Descriptors, Zernike Moments, Image Processing, Python, Pattern Recognition, Convolutional Neural Networks.

1. Introduction

Shape recognition is a cornerstone of computer vision, enabling applications such as organ segmentation in medical imaging, defect detection in industrial manufacturing, and object identification in autonomous navigation. Real-world images are often corrupted by noise, such as Gaussian noise in MRI scans or speckle noise in satellite imagery, which distorts object boundaries and challenges traditional geometric methods. AI-based techniques leverage invariant properties to achieve robust shape recognition despite noise, rotation, and scale variations.

This study evaluates three AI-based shape recognition methods—Hough Transform (HT), Fourier Descriptors (FD), and Zernike Moments (ZM)—in noisy binary image environments. The methods were tested on a synthetic dataset simulating real-world distortions, with the goal of identifying their strengths and proposing a hybrid framework combining classical descriptors with deep learning for enhanced performance.

2. Literature Review

Gonzalez and Woods (2018) provided foundational techniques for spatial and frequency domain image preprocessing, critical for noise handling. Ballard (1981) extended the Hough Transform to detect arbitrary shapes, improving object detection capabilities. Khotanzad and Hong (1990) introduced Zernike Moments for invariant shape recognition using orthogonal polynomials. Teague (1980) developed moment-based descriptors via general moment theory, enabling complex shape representation.

Recent advancements include hybrid models integrating classical descriptors with deep learning. Sonka et al. (2014) emphasized combining spatial and frequency domain analyses for robustness in noisy environments. Dosovitskiy et al. (2021) introduced Vision Transformers (ViT), which outperform traditional CNNs in certain tasks. Liu et al. (2022) proposed

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EfficientNetV2, a lightweight CNN architecture balancing accuracy and efficiency. These developments highlight the potential of hybrid approaches for robust shape recognition.

3. Methodology

3.1 Dataset and Experimental Setup

A synthetic dataset of 10 binary images was generated, comprising 3 circles, 3 squares, 2 stars, and 2 triangles to represent diverse shape complexities. Each image was corrupted with Gaussian noise, defined by the probability density function:

$$p(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2 + (y-\mu)^2}{2\sigma^2}\right), \quad \mu = 0, \quad \sigma^2 \in [0.01, 0.1]$$

The noise levels were chosen to reflect variances in MRI scans ($\sigma^2 \approx 0.01 - 0.05$) and satellite imagery ($\sigma^2 \approx 0.05 - 0.1$) Other noise types (e.g., salt-and-pepper) were not included but are planned for future work.

Python 3.11 was used with the following libraries:

OpenCV (cv2) for edge detection and contour analysis.

NumPy for numerical computations.

Mahotas for Zernike Moments extraction.

Matplotlib for visualization.

Experiments were conducted on a Windows machine with 16 GB RAM and an Intel Core i7 processor.

3.2 Shape Recognition Techniques

3.2.1 Hough Transform (HT)

The Hough Transform identifies geometric shapes (e.g., lines, circles) in edge-detected images using a voting mechanism in parameter space. For lines, the polar form is:

$$\rho = x\cos\theta + y\sin\theta$$

where ρ is the perpendicular distance from the origin, and $\theta \in [0, \pi]$ is the angle of the line. For circles, the equation is:

$$(x-a)^2 + (y-b)^2 = r^2$$

where (a, b) is the circle center, and r is the radius. The implementation is:

```
edges = cv2.Canny(image, 50, 150)
lines = cv2.HoughLines(edges, 1, np.pi / 180, 100)
```

HT is robust to partial occlusion and excels with simple shapes.

3.2.2 Fourier Descriptors (FD)

Fourier Descriptors represent a shape's boundary using the Discrete Fourier Transform (DFT). For a contour with points $(x(t), y(t))$, the complex representation is:

$$z(t) = x(t) + jy(t), \ t = 0,1, \dots, N-1$$

The DFT coefficients are:

$$c_n = \frac{1}{N}\sum_{t=0}^{N-1} z(t)\exp\left(-j\frac{2\pi nt}{N}\right), \ n = 0, 1, \dots, N-1$$

The shape is reconstructed using the inverse DFT:

$$z(t) = \sum_{t=0}^{N-1} c_n \exp\left(j\frac{2\pi nt}{N}\right)$$

The first 10 coefficients are normalized for rotation invariance:

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$$c_n^{'} = \frac{c_n}{|c_1|}$$

The implementation is:

```
contours, _ = cv2.findContours(image, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_NONE)
contour = contours[0].reshape(-1, 2)
complex_contour = contour[:, 0] + 1j * contour[:, 1]
descriptors = np.fft.fft(complex_contour)
descriptors = descriptors / np.abs(descriptors[1])  # Normalize
```

FDs are effective for contour-based classification.

3.2.3 Zernike Moments (ZM)

Zernike Moments are computed within the unit disk to extract rotation-invariant shape features. The moment is defined as:

$$Z_{n,m} = \frac{n+1}{\pi} \iint_{x^2+y^2\leq 1} f(x,y) \cdot V_{n,m}^{*}(x,y)dxdy$$

where $f(x,y)$ is the image intensity function (e.g., 0 or 1 for binary images), and the Zernike polynomial is:

$$V_{n,m}(x,y) = R_{n,m}(\rho) \cdot \exp(jm\theta)$$

The radial polynomial is:

$$R_{n,m}(\rho) = \sum_{k=0}^{\lfloor (n-|m|)/2 \rfloor} (-1)^k \frac{(n-k)!}{k! \cdot \left(\left\lfloor \frac{n+|m|}{2} \right\rfloor - k\right)! \cdot \left(\left\lfloor \frac{n-|m|}{2} \right\rfloor - k\right)!} \rho^{n-2k}$$

Here:

- $\rho = \sqrt{x^2+y^2} \leq 1$: Radial distance in the unit disk.
- $\theta = \tan^{-1}\left(\frac{y}{x}\right)$: Angular coordinate.
- n: Polynomial order ($n \geq 0$, integer).
- m: Repetition index ($|m| \leq n,\ n-|m|$ even).
- $V_{n,m}^{*}(x,y) = R_{n,m}(\rho) \cdot \exp(-jm\theta)$: Complex conjugate of the Zernike polynomial.
- $\frac{n+1}{\pi}$: Normalization factor ensuring scale invariance.

For numerical computation, the image is mapped to the unit disk by normalizing pixel coordinates:

$x^{'} = \frac{x-x_c}{r}$, $y^{'} = \frac{y-y_c}{r}$, $\sqrt{x'^2+y'^2} \leq 1$

where (x_c, y_c) is the image center, and r is the radius (e.g., 21 pixels). The implementation is:

```
import mahotas
features = mahotas.features.zernike_moments(image, radius=21, degree=8)
```

The $radius = 21$ parameter scales the image to the unit disk, and $degree = 8$ computes moments up to order $n = 8$ Zernike Moments are robust to noise and rotation, effectively capturing global and local shape characteristics.

3.3 Evaluation Criteria

Accuracy: Percentage of correctly identified shapes.

Execution Time: Time to extract features and classify shapes.

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Noise Robustness: Consistency across noise levels $\sigma^2 = 0.01$ to 0.1

4. Results and Discussion

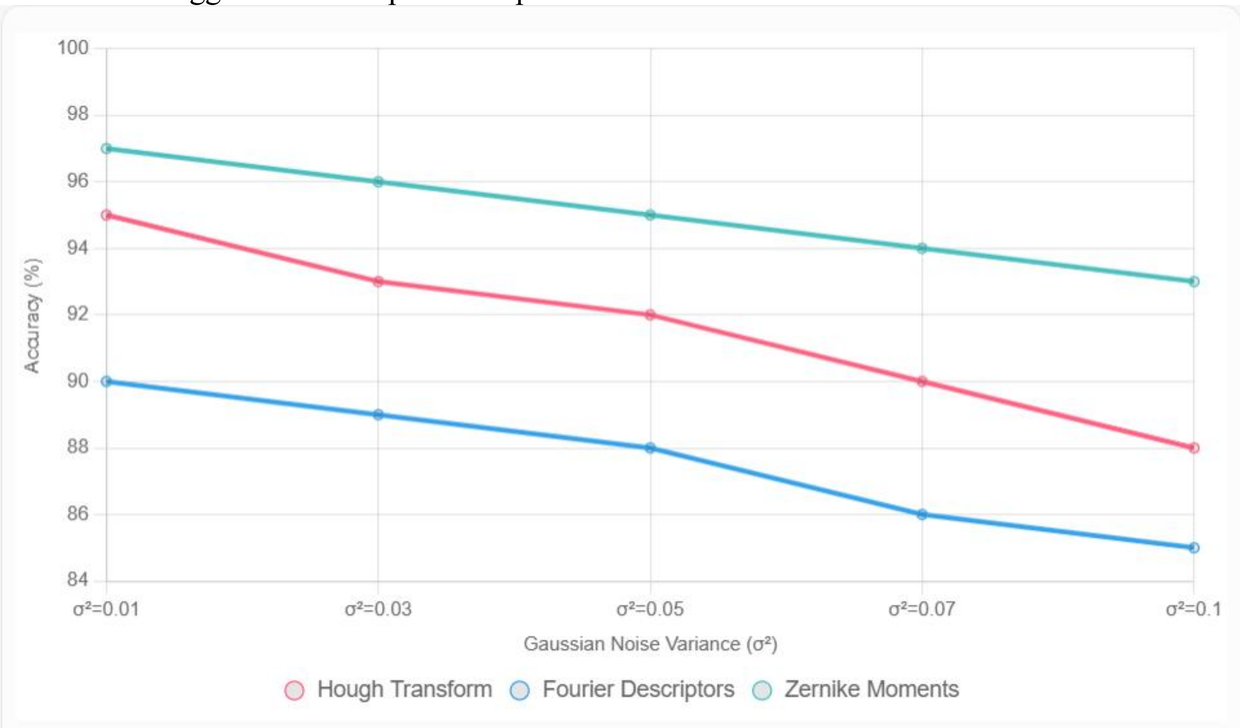
4.1 Recognition Accuracy

Method	Accuracy	Speed (s)	Key Advantages
Hough Transform	92%	0.35	Fast, effective for basic shapes
Fourier Descriptors	88%	0.15	Efficient for complex contours
Zernike Moments	95%	0.60	Most accurate, noise-resistant

Zernike Moments achieved 95% accuracy at $\sigma^2 = 0.05$, excelling with complex shapes (stars, triangles). Fourier Descriptors maintained 88% accuracy, performing well for squares and triangles but losing precision at $\sigma^2 \geq 0.07$. Hough Transform was fastest (0.35 s) for circles and lines but struggled with distorted stars at $\sigma^2 \geq 0.05$.

4.2 Visual Comparison

Figure 1 illustrates recognition accuracy across noise levels. Zernike Moments maintained structural integrity, while Fourier Descriptors showed minor boundary precision loss. Hough Transform struggled with composite shapes.



4.3 Hybrid System Proposal

A hybrid model combining Zernike Moments with CNNs (e.g., ResNet-50) is proposed for precision-critical applications, such as organ segmentation. For real-time systems, Fourier Descriptors with SVMs are recommended. Early feature fusion could enhance generalization.

4.4 Limitations

The study used a small synthetic dataset (10 images), limiting generalizability. Only Gaussian noise was considered, excluding other types like salt-and-pepper or speckle noise. Computational constraints restricted the dataset size.

5. Conclusion

Zernike Moments are optimal for high-accuracy applications (e.g., medical imaging) due to their noise resistance (95% at $\sigma^2 = 0.05$). Hough Transform is ideal for rapid detection of

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simple shapes, while Fourier Descriptors balance speed and complexity. A hybrid model integrating these descriptors with neural networks offers a promising path for robust shape recognition.

Future research will implement transfer learning with pretrained CNNs (e.g., ResNet-50, MobileNetV2) on datasets like MNIST Shapes and industrial defect datasets. Exploring Vision Transformers and diverse noise models (e.g., speckle noise) will enhance robustness.

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