Laboratory Practice 6 Mini Project Report NLP

Title

Feature Extraction using Zernike Moments

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Problem Statement

In the realm of image processing, extracting meaningful features that are invariant to transformations such as rotation is crucial for accurate object recognition. This project aims to implement a feature extraction technique using Zernike Moments, which are known for their rotation invariance and robustness, to effectively represent and classify shapes within images.

Introduction

Feature extraction is a fundamental step in image analysis, enabling the transformation of raw image data into a set of descriptors that can be used for various tasks like classification and recognition. Zernike Moments, derived from orthogonal polynomials, provide a powerful method for capturing shape information in images. Their rotation invariance makes them particularly suitable for applications where the orientation of objects may vary. This project focuses on leveraging Zernike Moments to extract features from images and assess their effectiveness in representing shape information.

Objectives

- To understand the mathematical foundation and properties of Zernike Moments in the context of image processing.

- To implement a feature extraction pipeline using Zernike Moments for capturing shape descriptors from images.

- To evaluate the effectiveness of Zernike Moments in representing and classifying shapes within images.

Methodology

The project follows a systematic approach to extract and utilize Zernike Moments for feature representation:

- Image Acquisition: Collect or create a dataset of images containing various geometric shapes.

- Preprocessing: Convert images to grayscale, resize them to a uniform size, and apply thresholding to obtain binary images.

- Feature Extraction: Utilize the Mahotas library to compute Zernike Moments for each preprocessed image.

- Feature Analysis: Analyze the extracted feature vectors to assess their ability to represent different shapes.

- Classification (Optional): Use machine learning algorithms to classify shapes based on the extracted features.

Tools and Technologies Used

- Python 3.x
- OpenCV
- Mahotas
- NumPy
- Matplotlib
- Scikit-learn (Optional)

Algorithm

1. Load Image: Read and convert to grayscale.

2. Resize Image: Standardize image dimensions.

3. Thresholding: Convert to binary image.

4. Compute Zernike Moments using Mahotas.

5. Extract the magnitude of the moments.

6. Classification (Optional): Use extracted vectors with a classifier.

Dataset Used

A custom dataset comprising images of basic geometric shapes such as circles, triangles, squares, and rectangles was created. Each image was processed to obtain a binary representation suitable for computing Zernike Moments. Additionally, variations of these shapes with different orientations were included to test the rotation invariance.

Implementation

The implementation was carried out in Python, utilizing the Mahotas library for computing Zernike Moments. Below is a sample code snippet:

```
import cv2
import mahotas
import numpy as np
image = cv2.imread('shape.png', cv2.IMREAD_GRAYSCALE)
image = cv2.resize(image, (128, 128))
_, binary_image = cv2.threshold(image, 127, 255, cv2.THRESH_BINARY)
zernike_moments = mahotas.features.zernike_moments(binary_image, 64)
print(zernike_moments)
```

Conclusion

The project successfully demonstrated the use of Zernike Moments for feature extraction in image processing. The extracted features effectively captured the shape information of objects in images and exhibited robustness to rotation, validating the rotation invariance property of Zernike Moments. This approach can be extended to more complex datasets and integrated with classification algorithms for applications in object recognition.