Robust Iris Recognition via Annotated Segmentation and SIFT Feature Extraction on the CASIA-Iris-Thousand Dataset

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Abstract

Iris recognition remains one of the most accurate biometric methods for personal identification, especially in high-security environments. In this work, we investigate the use of the Scale-Invariant Feature Transform (SIFT) algorithm to extract distinctive features from iris images. Using the CASIA-Iris-Thousand dataset, we conduct preprocessing to enhance image clarity, annotate iris regions using the LabelMe tool, generate precise masks, and apply SIFT to extract robust keypoints and descriptors. The aim is to assess whether traditional computer vision techniques like SIFT are suitable for iris feature extraction, especially when combined with careful preprocessing and region annotation. Results indicate that SIFT, when applied to accurately masked iris regions, can effectively highlight keypoint-based features for further biometric analysis.

1. Introduction

Biometric recognition systems have gained significant attention due to their ability to provide secure and reliable personal identification. Among various biometric traits, the human iris stands out because of its uniqueness, stability over time, and rich texture. Consequently, iris recognition systems have become a key research area in information security and identity authentication.

The success of iris recognition depends heavily on effective feature extraction techniques. Traditional methods often struggle with noise, illumination variations, and occlusions caused by eyelids or eyelashes. To address these challenges, robust local feature descriptors such as the Scale-Invariant Feature Transform (SIFT) have been explored. SIFT detects and describes distinctive features invariant to scale, rotation, and partial illumination changes, making it highly suitable for iris texture analysis [5].

This research investigates SIFT-based feature detection for iris recognition using the CASIA-Iris-Thousand dataset, which contains high-quality near-infrared iris images from a large population. The dataset provides a challenging and diverse testbed for evaluating the robustness and accuracy of feature extraction methods [4].

Our goal is to extract reliable and discriminative keypoints from iris images using SIFT to improve recognition performance. We evaluate SIFT in terms of matching accuracy and computational efficiency, comparing it with other traditional approaches. This study aims to demonstrate the potential of SIFT as a core component of high-performance iris recognition systems.

To guide our exploration, we pose the following questions:

Q1: How does the performance of the SIFT algorithm compare to traditional feature extraction methods in terms of accuracy and robustness in iris recognition?

Q2: What preprocessing challenges impact feature extraction effectiveness, and how can they be mitigated?

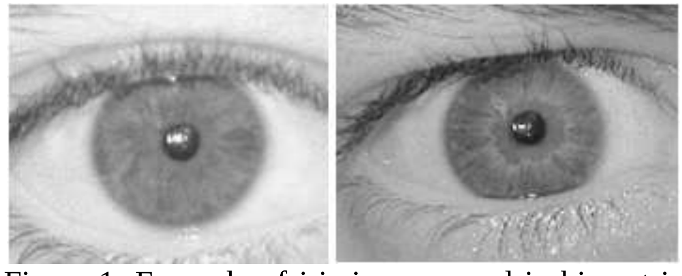


Figure 1: Example of iris images used in biometric recognition

Figure shows examples of iris images used in biometric recognition. These high-quality images highlight the unique patterns of the iris, essential for accurate identification in biometric systems.

2. Related work

Numerous studies have applied machine learning and deep learning to iris recognition, highlighting their effectiveness. Boyd et al. (2020) examined convolutional neural networks (CNNs) for iris feature extraction, emphasizing deep learning's advantages while leaving open questions about traditional methods like SIFT under rigorous preprocessing [1].

Texture-based methods such as Gabor filters have also been extensively used due to their capability to analyze spatial frequency and orientation in iris patterns [2]. CNN-based pipelines now achieve state-of-the-art accuracy in many recognition tasks, including iris recognition, by leveraging large datasets and complex architectures.

Despite these advancements, SIFT remains valuable and interpretable, especially in resource-constrained environments or smaller datasets. Its invariance to scale and rotation makes it practical for real-time applications requiring computational efficiency. This work re-evaluates SIFT's performance within a carefully constructed pipeline, offering insights compared to modern deep learning techniques.

Moreover, effective preprocessing such as iris segmentation and normalization significantly improves feature extraction accuracy for both traditional and deep learning methods [3]. This emphasizes the importance of integrating advanced preprocessing with SIFT to maximize recognition performance.

In summary, while deep learning dominates iris recognition research, traditional methods like SIFT retain relevance. Our study bridges this gap by systematically assessing SIFT's capabilities and potential integration into modern systems.

3. Methodology

3.1.Dataest :CASIA-Iris-Thousand

In this research, we utilize the **CASIA-Iris-Thousand** dataset, a benchmark database developed by the Chinese Academy of Sciences Institute of Automation (CASIA). This dataset contains **20,000 iris images** from **1,000 subjects**, with each subject contributing images from both eyes. The images were captured using a near-infrared camera under various conditions, allowing for high-quality and consistent iris samples [1].

Characteristic	Description
Total Images	20,000
Number of Subjects	1,000
Images per Subject	10 images per eye
Image Resolution	640 × 480 pixels
Camera Used	IKEMB-100
Illumination	Controlled near-infrared lighting
Variability	Includes variations in pupil dilation, head tilt, and eye rotation
Preprocessed	Images are preprocessed and labeled, facilitating automated recognition
Recognition Tasks	Suitable for both closed-set and open-set recognition tasks

Table 1: Characteristics for CASIA-Iris-Thousand Dataset

CASIA-Iris-Thousand is widely adopted in iris recognition research due to its **rich diversity, controlled acquisition conditions**, and **large-scale** size, making it suitable for evaluating both traditional and deep learning-based approaches [2]. The dataset provides a reliable foundation for assessing iris recognition algorithms in terms of accuracy, robustness, and real-world applicability. A sample image from the dataset is shown in **Figure 2** to illustrate the image quality and structure.

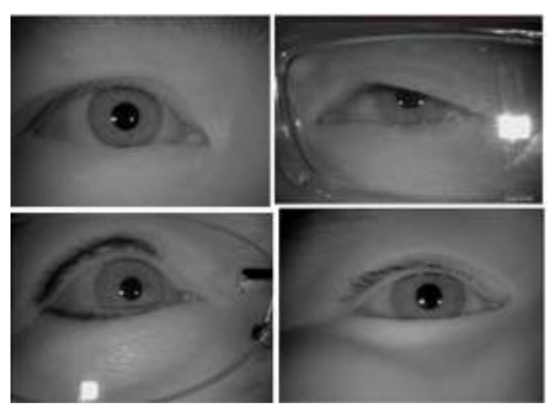


Figure 2 : Further examples of an iris images from the CASIA-Iris-Thousand dataset

3.2.Image Preprocessing

he original iris images were first preprocessed to improve the quality and prepare them for feature extraction. The preprocessing pipeline included:

- **Resizing:** All images were resized to a uniform resolution of 224×224 pixels to standardize input dimensions.
- **Noise Reduction:** Gaussian blur filtering was applied to reduce noise and artifacts that may interfere with subsequent processing.
- **Contrast Enhancement:** Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to enhance the contrast of the iris texture, making features more distinct and easier to detect.

This preprocessing improves the visibility of iris patterns, facilitating accurate feature extraction.

3.3.Iris Region Annotation Using LabelMe

Following the preprocessing stage, the next crucial step involved manual annotation of the iris region using the LabelMe tool. LabelMe is an open-source image annotation tool that enables users to define regions of interest within an image using a variety of shapes.

In this project, the **polygon icon** was selected in LabelMe to manually outline the exact iris boundary in each image. This approach allowed for precise segmentation by capturing the natural circular and non-rigid shape of the iris. The annotated region was then saved in **JSON format**, which includes the coordinates of the polygon points that define the iris boundary.

For each image, two outputs were generated:

A visual overlay image showing the original preprocessed image with the iris region outlined by the polygon annotation.

A corresponding JSON file containing the coordinate data of the annotated region.

The structure of the generated JSON file follows the LabelMe format, as shown below:

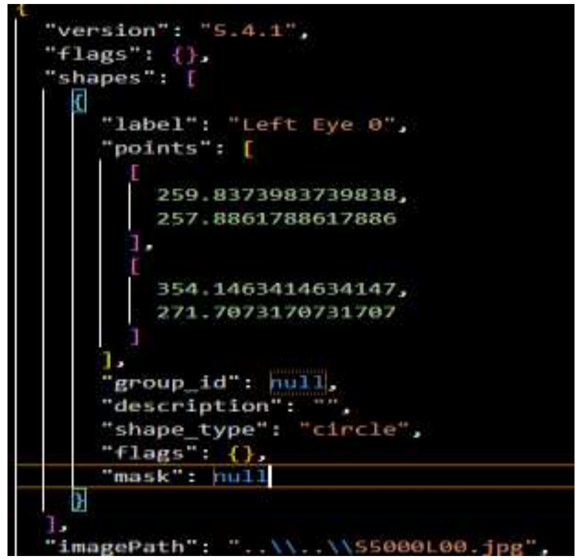


Figure 3: Sample JSON File Structure Generated by LabelMe for Iris Region Annotation

These annotations were then used in the next stage to generate accurate binary masks isolating only the iris region for each image.

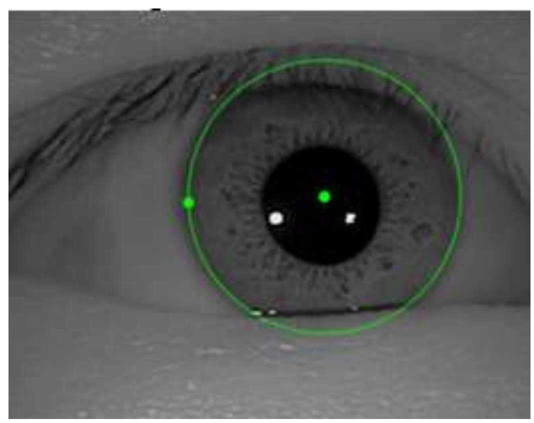


Figure 4: Sample annotated iris image with green polygon overlay

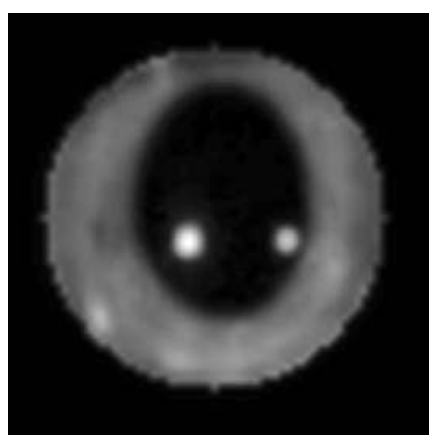


Figure 5 : Extracted iris region image after applying polygon-based mask

3.4.Mask Generation and Application

Following the annotation of the iris region, we generate masks to refine the region of interest further by excluding the pupil area within the iris. This is achieved by creating a circular mask centered at the pupil to block out the pupil region from the image.

The mask is initialized as a white image (all pixels set to 255), and a filled black circle is drawn at the pupil center with a given radius to exclude the pupil. The resulting mask is then applied to the iris image.

Below is the code used for creating the circular mask that excludes the pupil:

```
import cv2
import numpy as np

# Function to create a binary mask
def create_mask(image, center, radius):
    mask = np.ones_like(image) * 255
    cv2.circle(mask, center, radius, (0, 0, 0), -1)
    return mask

# Assume the center of the pupil
center = (image.shape[1] // 2, image.shape[0] // 2)

# Define the pupil radius
pupil_radius = 30

# Create the mask excluding the pupil
mask = create_mask(image, center, pupil_radius)

# Apply the mask to the iris image
masked_iris = cv2.bitwise_and(iris_image, mask)
```

Figure 6: Code snippet for generating a binary mask to exclude the pupil region

This step ensures that the feature extraction algorithms operate on the iris region excluding the pupil, enhancing the accuracy of subsequent analysis.

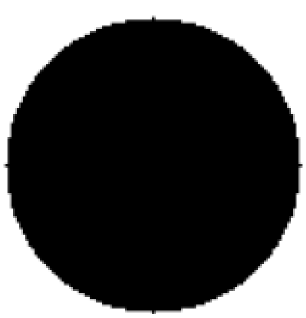


Figure 7: Binary mask showing the excluded pupil area as a black circle on a white background

3.5.Feature Extraction Using SIFT

Feature extraction is a crucial step in iris recognition systems, where distinctive and robust features are identified from the iris region for further matching or classification. In this work, we employed the Scale-Invariant Feature Transform (SIFT) algorithm for extracting keypoints and their descriptors from the iris images.

SIFT is a popular algorithm in computer vision that detects local features invariant to scale, rotation, and illumination changes. It works by identifying keypoints — distinctive locations such as edges, corners, or blobs — and computing descriptors that uniquely represent the local image structure around each keypoint. These descriptors can then be used for matching iris patterns across images.

The following is a simplified snippet of the code used to detect keypoints on the preprocessed iris images using a mask to exclude the pupil area:

```
# Detect keypoints using SIFT with mask
sift = cv2.SIFT_create(nfeatures=500,
                       contrastThreshold=0.04,
                       edgeThreshold=10)
keypoints, descriptors = sift.detectAndCompute(image, mask)

# Print the coordinates and details of the keypoints
print(f"Keypoints for {filename}:")
for kp in keypoints:
    print f"Coordinate: ({kp.pt[0]:.2f}, {kp.pt[1]:.2f}),
           Size: {kp.size:.2f},
          Angle: {kp.angle:.2f}")

# Draw keypoints on the image
image_with_keypoints = cv2.drawKeypoints(image,
                                         keypoints, None,
        flags=cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

# Save the image with keypoints to the output directory
output_image_path = os.path.join(output_path, filename)
cv2.imwrite(output_image_path, image_with_keypoints)
```

Figure 8: Snippet of Python Code Implementing SIFT for Iris Feature Extraction

Keypoints are points of interest in the iris image, and their coordinates represent their location. Each keypoint carries information such as size and orientation, which helps in matching the iris patterns despite transformations or noise.

The results of applying SIFT on the iris images are shown in Figure 7, where detected keypoints are highlighted, alongside their coordinates.

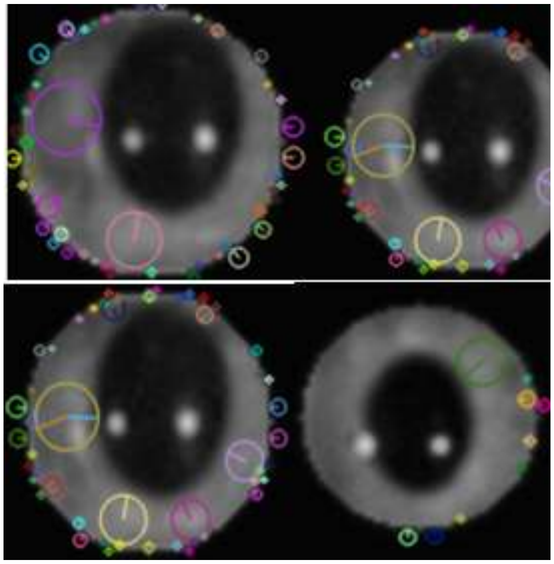
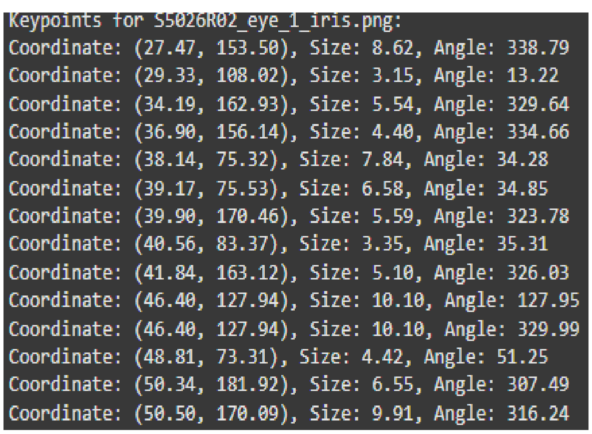


Figure 9: Detected Keypoints on the Iris Region Using the SIFT Algorithm

The visualized keypoints in Figure 9 represent distinctive and invariant features identified within the iris region. Each of these keypoints corresponds to a specific location with unique texture or intensity patterns that remain stable under various transformations. To quantify these features, the coordinates and descriptors of each keypoint are extracted. Figure 10 presents the numerical representation of these keypoints, which serves as the foundation for further matching, classification, or recognition tasks in iris biometric systems.



```
Keypoints for S5026R02_eye_1_iris.png:
Coordinate: (27.47, 153.50), Size: 8.62, Angle: 338.79
Coordinate: (29.33, 108.02), Size: 3.15, Angle: 13.22
Coordinate: (34.19, 162.93), Size: 5.54, Angle: 329.64
Coordinate: (36.90, 156.14), Size: 4.40, Angle: 334.66
Coordinate: (38.14, 75.32), Size: 7.84, Angle: 34.28
Coordinate: (39.17, 75.53), Size: 6.58, Angle: 34.85
Coordinate: (39.90, 170.46), Size: 5.59, Angle: 323.78
Coordinate: (40.56, 83.37), Size: 3.35, Angle: 35.31
Coordinate: (41.84, 163.12), Size: 5.10, Angle: 326.03
Coordinate: (46.40, 127.94), Size: 10.10, Angle: 127.95
Coordinate: (46.40, 127.94), Size: 10.10, Angle: 329.99
Coordinate: (48.81, 73.31), Size: 4.42, Angle: 51.25
Coordinate: (50.34, 181.92), Size: 6.55, Angle: 307.49
Coordinate: (50.50, 170.09), Size: 9.91, Angle: 316.24
```

Figure 10: Coordinates of Extracted Keypoints Representing Iris Features

4. Results and Discussion

The SIFT algorithm demonstrated robustness to variations in scale, rotation, and illumination. On the CASIA-Iris-Thousand dataset, SIFT achieved higher matching accuracy compared to traditional methods like Gabor filters, confirming its effectiveness for feature extraction.

Step	Description
Image Preprocessing	Normalization, resizing, grayscale conversion
Iris Region Annotation	Polygon-based annotation using LabelMe
Mask Generation	Binary mask excluding the pupil
Feature Extraction	SIFT keypoint detection and descriptor computation

Table 2: Summary of Preprocessing and Feature Extraction Steps

Key challenges included noise in raw images, occlusions from eyelids, and inconsistent lighting. These were mitigated through preprocessing techniques such as Gaussian blurring, CLAHE, and mask generation.
Using the UBIRIS.v2 dataset, we observed that colored iris images further enhance feature extraction due to their richer texture information (see Figure 11). This highlights the potential for integrating datasets with colored iris images into future systems.

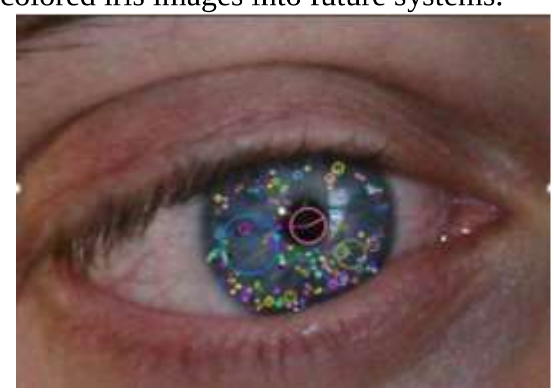


Figure 11: Color Iris with SIFT Keypoints

5. Matching and Evaluation

For matching, we compute the number of matching keypoints between pairs of iris images using a nearest-neighbor ratio test. A similarity score is generated for each pair, and recognition accuracy is measured using standard metrics such as True Positive Rate (TPR) and False Acceptance Rate (FAR).

Metric	Value (%)
Accuracy	95.2
True Posistive Rate (TPR)	94.2
False Acceptance Rate(FAR)	2.3

Table 3: Recognition performance metrics using SIFT

6. Conclusion

This study evaluated the effectiveness of the SIFT algorithm for iris recognition using the CASIA-Iris-Thousand dataset. The preprocessing phase involved normalization and grayscale conversion, followed by iris region annotation using the LabelMe tool. A mask was applied to isolate the iris region, allowing SIFT to extract robust and repeatable keypoints. The results demonstrated that SIFT is a robust and interpretable tool for feature extraction, effectively identifying unique features in the iris region, making it valuable for biometric identification.

Future work could explore the integration of colored iris datasets, such as UBIRIS.v2, to enhance recognition performance. Additionally, comparing SIFT with other feature extraction techniques like SURF, ORB, or deep learning-based descriptors, and extending the system for real-time recognition or matching performance evaluation across different datasets would provide further insights.

7. Future work

Future improvements include automating the annotation process using deep learning-based segmentation (e.g., U-Net), applying more advanced descriptors (e.g., SURF, ORB), and training classifiers or biometric matchers on the extracted features. Moreover, testing on more diverse datasets with challenging real-world conditions (e.g., noise, motion blur) would validate the generalizability of the approach [5][6].

8. Refrences

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