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Iris Segmentation from Digital Image Using Content Features and Genetic Algorithm

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***Abstract* – Biometric identification using eye images relies heavily on accurate iris detection. Localizing the iris region from other parts of the eye is a challenging task, as eye images vary significantly across individuals and can also change over time due to lighting, pose, and image quality. This paper presents an iris segmentation approach that combines both color and edge features to improve detection accuracy. The segmentation process primarily depends on selecting appropriate color features to identify the iris region. A hybrid optimization strategy, integrating the Butterfly Algorithm with Particle Swarm Optimization, is employed to determine optimal cluster centers for iris localization. The use of this hybrid genetic-based approach enhances the accuracy of color feature detection. Once the relevant features are identified, edge information is used to locate the circular structure of the iris. Although the iris is not a perfect circle, the surrounding region is also included to ensure complete coverage of the iris area. Experimental validation was carried out on real-world datasets containing both left and right eye images, demonstrating the effectiveness of the proposed method.**

***Keywords* – Iris recognition, Image Segmentation, Genetic Algorithm, Feature Optimization.**

I. INTRODUCTION

The iris is the colored circular region surrounding the pupil of the eye. Similar to fingerprints, iris patterns are formed during fetal development and remain unique to each individual, even in the case of identical twins. One may observe that in very elderly individuals, despite visible aging of the skin, the eyes often retain a youthful appearance. This is because the iris structure remains essentially unchanged throughout a person's lifetime, preserving the same pattern from youth to old age [1]. Owing to its stability and uniqueness, the iris is widely used for both personal verification and identification. However, iris recognition is generally unsuitable for surveillance applications, as capturing high-quality iris images requires close proximity and the subject's cooperation.

A typical iris recognition system is composed of three primary components: image acquisition, preprocessing, and feature extraction with encoding. The image acquisition stage involves capturing iris images using specialized sensors or cameras [2]. The preprocessing stage focuses on locating the iris boundaries within the eye image and isolating the iris region to enable effective analysis [3,4]. This stage includes processes such as iris segmentation, normalization, and image enhancement. Although significant progress has been made in edge and boundary detection techniques, achieving consistently high segmentation accuracy remains challenging. Consequently, there is a strong need for more robust and reliable iris segmentation methods.

Several techniques have been proposed for iris localization and segmentation, including the Hough transform [3], Active Contours [4], and GrowCut algorithms [5]. However, these traditional methods often perform poorly when applied to low-quality or degraded images. In contrast, deep learning approaches—particularly Convolutional Neural Networks (CNNs)—have demonstrated remarkable success in image-related tasks such as classification [6] and object detection [7]. CNNs are capable of automatically learning hierarchical semantic features from input images in an end-to-end manner, without requiring manual feature design. With the rapid advancement of deep learning, numerous studies have employed CNN-based models for iris segmentation [8], iris bounding box detection [9], and pupil center localization.

This paper is organized into several sections. The first section introduces the research domain and its significance. The second section reviews existing iris detection and segmentation techniques proposed by various researchers. The third section presents the proposed methodology, supported by a block diagram and detailed explanations of each component. The performance of the proposed model is then evaluated and compared with existing methods using standard evaluation metrics. Finally, the paper concludes by summarizing the key findings and outcomes of the proposed approach.

II. RELATED WORK

In [8], the authors introduced a high-efficiency deep learning–based iris segmentation framework known as IrisParseNet. Unlike many earlier CNN-based approaches that focus solely on generating accurate iris masks using conventional semantic segmentation models, this method offers a complete iris segmentation solution. It jointly estimates the iris mask along with parameterized inner and outer iris boundaries through a unified multi-task network. An attention mechanism is also incorporated to enhance segmentation accuracy. The model was trained and evaluated using three challenging and representative iris datasets—CASIA.v4-distance, UBIRIS.v2, and MICHE-I—which include variations in illumination (NIR and visible light), sensor types (long-range and mobile cameras), and noise conditions.

In [9], the authors proposed four novel network architectures, among which the Fully Dilated U-Net (FD-UNet) achieved the best performance when trained and tested on the same datasets. The FD-UNet replaces standard convolutions with dilated convolutions, enabling the network to capture more global contextual information while preserving fine image details, thereby improving segmentation quality.

The study in [10] presented a new multimodal biometric recognition approach that integrates maxout units into CNNs to generate compact feature representations for each modality. The discriminative features from iris and periocular modalities are then fused using a weighted concatenation strategy. Both the convolutional filter parameters and fusion weights are jointly learned, allowing the model to optimize a unified representation for improved biometric recognition.

In [11], the authors proposed a human identification framework that combines facial and iris biometrics extracted from low-resolution images, a scenario commonly encountered in long-distance recognition. To address the limitations caused by reduced image quality, a hybrid Log-Gabor–Legendre (LGL) filter was employed to enhance feature extraction from multispectral face and iris images. Following LGL filtering, the phase quadrant method was applied for iris recognition, while the Local Gabor Binary Pattern Histogram Sequence (LGBPHS) method was used for face recognition. The final identification decision was obtained through score-level fusion, resulting in improved recognition performance across multiple stages of the framework.

Finally, in [12], the authors introduced a new feature extraction technique for a multimodal face–iris biometric system. Polar Fast Fourier Transform was used to extract texture features at multiple scales and orientations from face and eye images. Canonical Correlation Analysis was then applied to fuse the face and iris feature sets, reducing the dimensionality of the combined feature vector while enhancing its discriminative capability. The proposed method effectively improves person recognition performance by exploiting complementary information from both facial and iris traits.

III. PROPOSED WORK

The entire work is organized into multiple modules that follow the sequential steps involved in transforming a user-provided eye image into the final iris recognition output. As illustrated in Fig. 1, the system is mainly divided into two major modules. The first module focuses on image preprocessing and the extraction of edge-based features, while the second module performs iris segmentation using a genetic algorithm. Since genetic algorithms are employed for segmentation, no prior information about the image, the user, or previously processed images is required.

First Module:

In the first module, the input image is refined to improve overall processing accuracy. As segmentation performance is highly dependent on image quality and features, this module carries out both preprocessing and feature extraction. During preprocessing, the input image is read and represented as a matrix with dimensions equal to that of the image, where each matrix element corresponds to the pixel value at that location. For example, a 2×2 image containing four pixels is represented by a 2×2 matrix with values reflecting the respective pixel intensities. To ensure uniformity across the dataset, all images are resized to a fixed dimension, as input images may originally vary in size. Additionally, all images are converted to grayscale [13], since color images such as RGB or HSV have three channels, whereas grayscale images are two-dimensional and more suitable for efficient feature extraction and segmentation.

Extraction of Visual Feature

In this work, visual edge features are extracted from the input iris image [14]. For edge detection, the Canny edge detection algorithm is employed due to its effectiveness in highlighting significant boundaries. The procedure includes smoothing the image using a Gaussian filter to suppress noise, computing the gradient magnitude and orientation through finite-difference approximations, applying non-maximum suppression to thin the edges, and finally using a double-thresholding technique to accurately detect and connect relevant edges.

Module 2: Genetic Algorithm

Population Generation:

In this step, an initial population is created by generating multiple chromosome sets, where each chromosome represents pixel values extracted from the edge regions of the iris image. Pixels with a feature value of zero are ignored, as they do not contribute to the segmentation task. Each selected set of pixel features forms a chromosome (Cc), and the collection of all such chromosomes constitutes the population (P).

Fitness Evaluation:

The quality of each chromosome is assessed using a fitness function that aims to identify the most suitable segmentation. This is achieved by computing the distances between pixel cluster centers and surrounding pixel values. Euclidean distance is used as the similarity measure to quantify differences between pixel intensities.

Euclidean Distance Measure:

Let X denote a pixel value corresponding to a cluster center within a chromosome, and let Y represent a neighboring pixel of the same image with an edge feature value of one. The distance between X and Y is calculated using the standard Euclidean distance formula (Eq. 2). The minimum distance obtained across all pixel sets and cluster centers determines the fitness score of each chromosome, with smaller distances indicating better solutions.

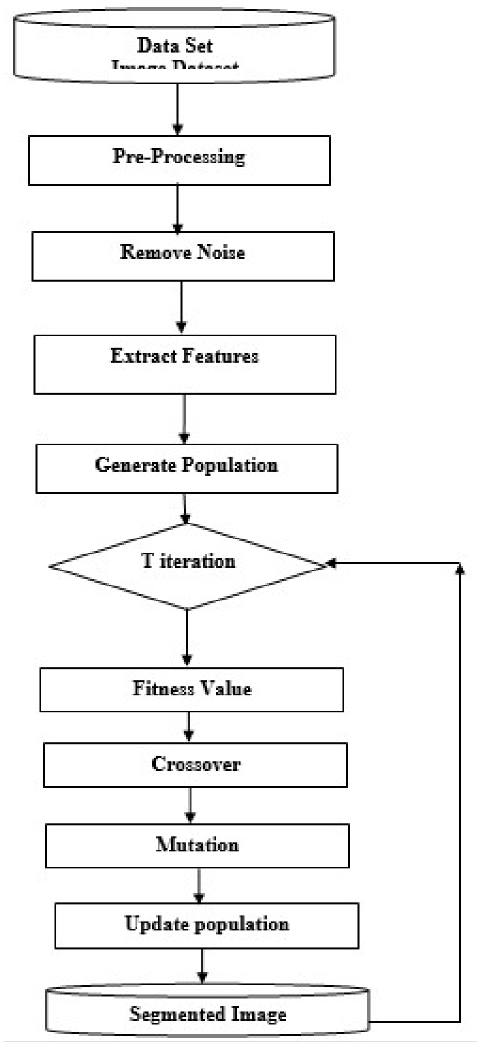

Fig. 1 Block diagram of proposed model.

Modified Genetic Algorithm Framework:
A generalized hybrid genetic optimization approach is adopted by incorporating concepts from evolutionary computation and swarm intelligence. Crossover operations are guided by sensitivity and adaptive parameters, while swarm-inspired concepts influence how solutions evolve across iterations. In this framework, control parameters regulate the number of crossover operations applied to chromosomes, while positional adjustments influence how candidate solutions are explored. Unlike classical swarm-based approaches, chromosome updates are not directly altered through positional displacement; instead, emphasis is placed on adaptive crossover strategies to refine solutions.

Crossover Operation:
The population is updated through structured crossover operations. Column-wise modifications help relocate potential cluster centers within a solution, allowing exploration of alternative segmentation patterns. Row-wise updates, influenced by locally best solutions, increase the likelihood of generating chromosomes with improved fitness values.

Global Best Update:
At the end of each iteration, the global best (G-best) solution is updated if a newly generated chromosome achieves a better fitness value than the current best. The iterative process continues until either no further improvement is observed over successive iterations or a predefined maximum number of iterations is reached.

Image Segmentation:
After completing the optimization process, the final set of optimized cluster centers is used to segment the image. The iris region is extracted based on representative segment pixels and is highlighted in white, while non-iris regions are marked in black, resulting in a clear binary segmentation of the iris area.

IV. EXPERIMENT AND RESULTS

The experimental analysis was carried out using MATLAB. All implementations were executed on a system running the Windows operating system, equipped with an Intel i3 processor and 4 GB of RAM. The performance of the proposed approach was evaluated by comparing it with the existing method reported in [2].

Dataset:
The iris images used for testing were obtained from the dataset described in [16]. A detailed summary of the dataset characteristics and the parameters of the iris images.

Results

Table 1. Precision value based comparison.

Image Set	Proposed Model	Previous Model
2	0.879383	0.782364
3	0.81702	0.808939
4	0.836013	0.780138
5	0.758591	0.758424

Table 1 presents a precision-based comparison between the proposed approach and the existing model. The results indicate that the proposed method identifies the iris region with higher precision across most image sets. The integration of the BAPSO algorithm improves precision by approximately 4.33% compared to the earlier method reported in [2]. Additionally, the use of a genetic algorithm for selecting cluster centers effectively eliminates the influence of the upper and lower eyelids, leading to more accurate iris localization.

Table 2. Recall value based comparison.

Image Set	Proposed Model	Previous Model
2	0.743658	0.911143
3	0.891318	0.891689
4	0.817308	0.973492
5	0.757615	0.754842

Table 2 summarizes the recall values for both methods. The results show that the proposed and existing models achieve comparable recall performance for most images, with only minor variations across datasets.

Table 3. F-Measure value based comparison.

Image Set	Proposed Model	Previous Model
2	0.805846	0.801857
3	0.852553	0.848301
4	0.826554	0.816156
5	0.758103	0.756629

Table 3 provides an F-measure comparison, which reflects the balance between precision and recall. The proposed model demonstrates a marginal improvement of about 0.6% over the previous approach. This enhancement can be attributed to the combined use of edge-based and color-based features, which together improve the overall accuracy of iris detection.

Table 4. Accuracy value based comparison.

Image Set	Proposed Model	Previous Model
2	81.805	78.7234
3	80.6983	79.929
4	81.8155	79.4477
5	74.8942	75.6686

V. CONCLUSIONS

Accurate detection of the iris from eye images is essential for many biometric and security-related applications. In this study, an iris segmentation approach based on a genetic algorithm is presented, where both edge and color features are extracted from the input image. The segmented output is then further processed to isolate the iris region more effectively. Experiments conducted on a large dataset demonstrate that the proposed method improves overall accuracy by 2.06% and enhances precision by 4.33% compared to existing approaches. Future research may explore alternative genetic algorithms and additional feature combinations to further improve iris region identification.

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