Fusion of Thresholding and Limbic Pupilliary Boundary Algorithms for Iris Segmentation Process

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ORIGINAL RESEARCH

Abstract—Iris segmentation is crucial in the development of an effective iris recognition system, it involves localizing relatively the exact region of the iris before its features are being extracted for matching. Several researches have used different algorithms for the segmentation of iris, however, traditional systems encounter challenges in accurately identifying individuals under varying conditions, primarily due to inaccurate segmentation. To address this, the study proposes an AI-based fusion technique combining Thresholding and Limbic Pupillary Boundary algorithms, aiming to enhance segmentation accuracy and reliability. Leveraging the eye images datasets from reputable sources and MATLAB implementation, the study improves segmentation performance, particularly in uncertain environments. The results are presented using histogram representation to demonstrate the efficacy of the fusion approach, contributing to advancements in iris recognition technology.

Keywords— Biometric, Iris recognition, Limbic Pupil Boundary, Segmentation, Thresholding.

1 Introduction

Iris segmentation is a critical and important phase in iris recognition systems. Segmentation correctly separates the iris area from other parts of the eye image, which facilitates effective feature extraction and detection (Malgheet et al., 2023). The segmentation ensures that the recognition system concentrates solely on the distinctive iris characteristics, resulting in more accurate and trustworthy identification. Moreover, the system's performance is markedly enhanced through accurate and robust iris segmentation. Inaccuracies in segmentation can have a direct impact on the performance of the entire identification system, leading to a 'failure to match' scenario during the recognition phase.

Additionally, when boundaries—particularly the limbus boundary—are obscured by elements such as eyelashes or eyelids, or when the pupil boundary is inaccurately located, crucial iris features may be absent from the extracted region. This absence has the potential to significantly undermine the performance of the comprehensive iris recognition system (Li et al., 2019). Consequently, precise segmentation elevates both the efficacy and dependability of the recognition process. Hence, the accuracy and reliability of the iris recognition system are profoundly influenced by the caliber of iris segmentation, exerting a substantial influence on the overall system performance.

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Section B- ELECTRICAL/COMPUTER ENGINEERING & RELATED SCIENCES

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Various segmentation approaches have been explored in the field of iris recognition system. (Ahmadi et al., 2017) effectively employed Canny edge detection to enhance grayscale image edges while using the Hough transformto precisely locate the pupil and limbus circles.

Similarly, (Nirgude et al., 2017) achieved precise iris region segmentation by combining Canny edge detection with the Hough transform technique.

However, traditional iris recognition systems face several difficulties despite having outstanding accuracy and reliability in biometric identification (Adamović et al., 2020). These difficulties result from their inability to correctly identify individuals in a range of environmental circumstances. The efficiency of these systems is severely hindered by factors like occlusions, illumination changes, and image quality variations.

These difficulties with iris recognition systems have serious effects and reduce their overall performance. Accurate identification depends on the ability to localize the iris from the segmented eye image, separate the iris pattern from the pupil area, and correctly separate the eye feature from the rest of the facial structure (Lo et al., 2020). Issues occur during the matching or verification process when segmentation is not accurate. Even users who have registered with the system are not immune to "failure to match" issues, which are primarily caused by improperly segmented irises.

To address these pressing issues, this study presents an AI based Iris Segmentation technique. This novel approach is based on the fusion of two carefully selected, proven approaches, which have been shown in the literature to be accurate and effective. This study intends to improve the iris segmentation process to reliably recognize people even in uncertain environmental situations, hence raising the overall reliability and effectiveness of the iris recognition system.

Iris recognition system has gained significant attention as a reliable and accurate biometric verification and identification technology (Adamović et al., 2020). The Iris recognition consist of five principal stages, Acquisition, localization/segmentation, normalization, feature extraction and matching stage.

Essentially, the recognition starts with image acquisition to the extraction and matching of the feature stage which prompt the decision of the recognition process.

As depicted in Figure 2.0, the iris recognition system consist of five stages. The first stage of iris recognition is image acquisition, where a high-quality iris image is captured using near-infrared light with specialized cameras. The eye images datasets adopted in this study are CASIA and UBIRIS datasets. The second stage involves segmentation, which involves separation of eye features from facial features and localizing the iris pattern accurately. The segmentation stage is the most crucial stage of the recognition process.

The segmentation stage is closely followed by normalization, where the segmented/localized iris pattern is transformed from Cartesian to Polar form for simpler representation and enhanced feature extraction. After normalization, feature extraction involves identifying and capturing the unique characteristics of the iris, this process also involves features encoding. These features are encoded into a compact bit-wise template, serving as a distinctive representation for efficient classification. The Last stage involves matching of the extracted features to the already stored features in the system database for individual recognition. The feature matching stage prompt the decision of the system.

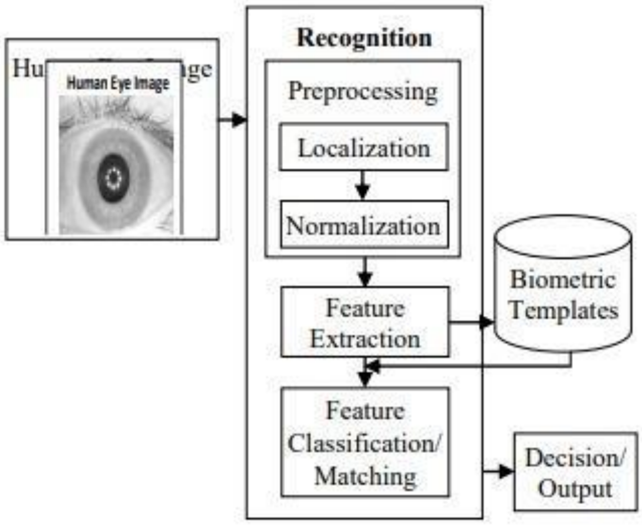

Figure 2.0: Iris Recognition System Process.

(Lo et al., 2020), (Saminathan et al., 2015), (Sarhan, 2009), (Shao & Xie, 2006) and (Zhang et al., 2004) proposed a novel iris recognition system using different methods for iris segmentation and localization.

(Lo et al., 2020) adopt the use of Convolutional Neural Network (CNN) for feature matching. The study normalized the segmented iris using Daugman's Rubber Sheet Model. The normalized iris features were encoded utilizing the Unit-Circle Layer. The matching process involved analyzing the similarity index between the encoded iris images. The findings of the study indicated that the CNN-based system exhibited superior accuracy in terms of True Acceptance Rate (TAR) and False Acceptance Rate (FAR) when compared to three other state-of-the-art iris verification algorithms (IrisCode, Ordinal, and UniNet). Additionally, the CNN-based system demonstrated effective adaptability to varying qualities of input iris images, enhancing its security for iris verification when appropriate threshold values were set.

In Zhang et al. (2004), the circular Hough transform is employed to achieve precise localization of the iris region within the image. Afterwards, the localized iris undergoes a transformation from polar coordinates to Cartesian coordinates to facilitate normalization. The feature extraction technique utilized in this study combines both local and global feature extraction methods. Global features are extracted using Log Gabor wavelet filters, while local features are extracted using Log Gabor filters. Weighted Euclidean distance and Hamming distance are employed for classification and matching purposes. The experimental results demonstrate that this framework significantly improves recognition speed and effectively reduces the false rejection rate (FRR) by harnessing the combined power of global and local features.

In Saminathan et al. (2015), a grayscale image from the CASIA database is utilized as the foundation for the experimental study. The iris image is localized through the combined utilization of Limbic Pupil Boundary (LPB), Canny Edge Detection, and Hough transform techniques. Subsequently, Daugman's Rubber Sheet model is applied to convert the iris image from Cartesian coordinates to Polar coordinates; thus, achieving a fixed-size representation. Unique features are extracted using a matrix template format. For classification and identification purposes, various methods including Hamming distance, local binary patterns, neural networks, and SVM are employed. Among these methods, SVM demonstrates superior performance compared to the others when utilizing three specific kernels and methods. Notably, the Quadratic kernel in combination with the Least Square Method exhibits the best performance. Through evaluation of the CASIA database, SVM is shown to be highly effective, achieving an accuracy of 98.5% with a zero False Acceptance Rate (FAR).

(Sarhan, 2009) presented a novel iris recognition system which utilizes the Discrete Cosine Transform (DCT) and Artificial Neural Network (ANN). The study utilizes a dataset comprising iris images from 30 individuals, specifically obtained from the CASIA database v2. DCT is applied to extract distinctive features from the iris images using both the square-window method and the zigzag method. Subsequently, a three-layer ANN is employed to classify the extracted feature vectors. Through experimental evaluation of the CASIA database, an

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impressive recognition accuracy of 96% is achieved. It is important to note that this high accuracy is obtained with minimal computational costs, as only 49 DCT coefficients are utilized.

(Shao & Xie, 2006) presented a novel approach to iris recognition, which incorporates a kernel classifier PCA and utilizes 2-level wavelets for noise reduction and feature extraction. The extracted features are subsequently classified using Support Vector Machine (SVM) and Kernel Fisher Discriminant (KFD). The study includes a comparative analysis between SVM and KFD, considering various kernel functions, using the CASIA database. The experimental results indicate that SVM, particularly when using a Gaussian kernel in conjunction with the One Against One (OAO) method, achieves the best performance with a false acceptance rate (FAR) of 0.42. Furthermore, a comparison with existing methods demonstrates that the proposed approach surpasses other established techniques.

In (Adamović et al., 2020), a system for iris recognition was presented, incorporating stylometric features and machine learning techniques. The localization of the iris was achieved through the utilization of the Hough transform and Canny edge detection. Subsequently, Daugman's Rubber Sheet Model was applied to normalize the localized iris region. To maintain the statistical properties of the iris image, the normalized iris was encoded as raw text using a Base64 encoder. The encoded features were then processed by a stylometric feature extractor, which extracted relevant characteristics for classification purposes. The system's performance was evaluated through experiments conducted on a CASIA database, and its generalization capability was tested on the IITD and MMU datasets using the SMOTE and Random Forest methods. The proposed approach demonstrated a notable level of accuracy in iris recognition.

(Vasavi & Abirami, 2020), (Journal & Ejt, 2016), (Buddharpawar & Subbaraman, 2015) and (Shrivas & Tuli, 2012) conduct a study that focuses on the recognition of human iris images based on their local texture structures. The iris images used in the studies were obtained from the CASIA database.

In the case of Vasavi & Abirami (2020) and Journal & Ejt (2016) they examine the utilization of machine learning techniques in iris recognition systems. The studies explore different algorithms employed in machine learning and supervised machine learning for classification of iris. The studies revealed that several techniques have been employed in the extraction of features, and deployed different means extraction after acquisition of datasets. (Buddharpawar & Subbaraman, 2015) also presents a proposed identification system that utilizes Principal Component Analysis (PCA) on the CASIA eye image datasets.

(Journal & Ejt, 2016) extract the texture features by dividing the iris image into four local regions and this is conducted by the application of the common GLCM (Grey-Level Co-occurrence Matrix) technique. A total of 88 parameters were extracted for each image as a feature vector. Then, the obtained feature vectors were classified using k-Nearest Neighbor (KNN) classifiers and the average performance of each system was compared according to different k values (1, 3, 5, 7 and 9). Finally, the best average performance among system architectures of iris recognition systems was observed as 85 % in the k=1 neighbor structure of the k-NN classifier. Meanwhile (Vasavi & Abirami, 2020) was able to analyze the process of recognition using extracted features vectors as input for any Machine learning classifiers algorithms and conducted analysis of the performance of different classifiers. The analysis of the classifiers reveals that SVM offers a succinct model for predicting class labels based on the iris features.

Also (Buddharpawar & Subbaraman, 2015) proposed a system involving the five processes of iris recognition system, the system conducted initial preprocessing of the iris image. Using the boundary method, the Gaussian filters was adopted for localization, application of Daugman's rubber sheets model to normalize the localized iris, and the use of histogram equalization to enhance the normalized iris. For feature extraction, PCA is employed and the feature vectors are matched using the Euclidean distance. Experimental analysis conducted on the CASIA database demonstrates that the system achieves an identification accuracy of 85% using the Euclidean distance metric. (Shrivas & Tuli, 2012) localized the iris region using circular Hough transform and also employed the Daugman rubber sheet to model the normalization of the localized iris.

In conclusion Vasavi & Abirami (2020), Journal & Ejt (2016), Buddharpawar & Subbaraman (2015) and Shrivas & Tuli (2012) showcased the potential of machine learning algorithms, local texture structures, and effective preprocessing techniques in achieving accurate and reliable iris recognition systems. Additionally, the use of the CASIA dataset in the reviewed studies adds credibility and relevance to presented findings; the consistent use of the CASIA datasets allows for comparisons between different approaches and methodologies, enabling researchers to identify the strengths and weaknesses of various techniques. This promotes the development of robust and reliable iris recognition systems that can be effectively applied in real-world scenarios.

Numerous AI methods have been developed to enhance iris recognition systems. Thakkar & Patel (2020) propose a novel approach that combines Gabor filters and deep learning. Their method utilizes Gabor filters to extract features from iris images, which are then fed into a supervised neural network, achieving an exceptional authentication accuracy of 99.99%. In a different study, Reyes-Lopez et al. (2012) compare Zernike and Pseudo-Zernike Polynomials with a Support Vector Machine

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(SVM) for iris image identification. The results indicate that the proposed method using Pseudo-Zernike Polynomials outperforms the one using Zernike Polynomials. Another method introduced by Nirgude & Gengaje (2017) involves feature extraction based on multi-resolution analysis. These extracted features are utilized for classification, employing the RBF kernel function for `1`recognition. Experimental results demonstrate improved recognition accuracy ranging from 76.3% to 95.33% due to the combination of iris details from different resolution levels. These studies contribute to the advancement of iris recognition by introducing innovative techniques and achieving significant improvements in accuracy.
However, the mostly used methods for segmentation and localization of iris are the LPB and Hough Transform. Hence, this study is fussing LPB with thresholding method of segmenting iris and evaluates the performance of the fusion.

2 METHODOLOGY

In the iris recognition system, segmentation plays a vital role in isolating the iris region by accurately identifying or detecting the iris boundaries (pupil and limbic) that separate the distinct iris features from the facial features. This process is essential, as it lays the foundation for the effectiveness of subsequent stages. This study proposed a fussion approach to specifically enhance the efficacy of iris segmentation, which has a direct impact on the overall performance of the iris recognition system.

2.1 DATA / IMAGE ACQUISITION

The success of an iris recognition system heavily depends on the quality of the datasets employed.
The datasets employed in this study were acquired from two reputable sources; the CASIA database and Kaggle repository.

2.1.1 CASIA

The CASIA (Chinese Academy of Sciences Institute of Automation) datasets are collections of iris images captured using a near-infrared camera with appropriate illumination. The CASIA database, a public database with several subsets or versions of iris images (CASIA-IrisV1, CASIA-IrisV2, CASIA-IrisV3, and CASIA-IrisV4), is widely utilized by researchers in the field of iris recognition systems. This study employed the CASIA-IrisV1, which comprises 756 iris images from 80 subjects.

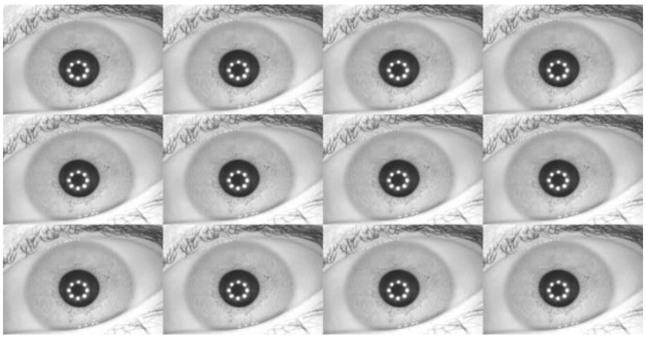

Figure 3.1: Eye Image Obtained from CASIA

2.1.2 KAGGLE:

Kaggle is an online community platform for data scientists and artificial intelligence enthusiasts. It provides various datasets in several domains for research, analysis, and model development. The Ayush dataset employed in this study comprises 650 eye images (325 blurred and 325 non-blurry each) for comparative analysis.

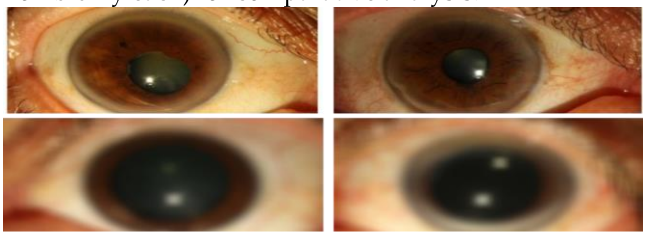

Figure3.2: Non- Blurry and Blurry Eye Image Obtained from Kaggle

2.2 IMAGE SEGMENTATION / LOCALIZATION

Image segmentation is a critical stage in iris recognition process, involve in localizing the iris region from the rest of the eye image.
In this study, a hybrid approach to iris segmentation is employed. It employs the combination of Thresholding and Limbic Pupil Boundary (LPB) to enhance the accuracy of iris segmentation. The system was developed with the use of MATLAB.
The thresholding is the initial step in the hybrid approach. It is employed in separating the iris region from the background by converting the grayscale/preprocessd iris into binary image with a specific threshold value of 0.5 being established. LPB is thus used to significantly improve the accuracy of segmentation result by passing the resulted image from thresholding segmentation as input for the LPB.
This study utilizes simple thresholding by comparing the value of each pixel in the image to a specific threshold value and it is executed by following the pseudocode attached herewith.

Thresholding Pseudocode
Step 1: Start
Step 2: Read the grayscale eye image.
Step 3: Initialize iteration count and threshold value (T) as mean intensity of the grayscale image.
Step 4: Repeat until convergence

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Step 5: Increment the iteration count.
Step 6: Create binary image (g) by comparing grayscale image with threshold value (T).
Step 7: Calculate next threshold value (Tnext) as average of pixel intensities in binary regions (g) and complementary regions (-g).
Step 8: Check if absolute difference between current threshold (T) and next threshold (Tnext) is less than convergence criterion (0.5).
Step 9: If convergence criterion is met, exit loop; otherwise, update T with Tnext and repeat.
Step 10: Convert binary image (g) to binary image with pixel values in range [0, 1].
Step 11: Display original eye image and its histogram representation.
Step 12: Display segmented iris image (g) and its histogram representation.
Step 13: Stop

The threshold pseudocode is programmed on MATLAB for both non-blurry and blurry eye images from the Ayush's dataset using the following code snippets.

Thresholding Code Snippet for Non-blurry Eye

```
ff= imread ("RECENT.jpeg");
f= imread("iris1.jpg");

count =0;
T= mean2(f);
done = false;
while (done)
   count =count +1;
   g= f>T;
   Tnext= 0.5*(mean(f(g)))+mean(f(-g));
   done = abs(T-Tnext)<0.5;
   T= Tnext;
end
g= im2bw(f, T/255);
imshow(f), title('Original Iris 1 image')
figure, imhist(f), title('Oroginal Iris 1 histogram')
figure, imshow(g), title('Iris 1 Segmented Image')
figure, imhist(g), title('Iris 1 Segmented histogram')
```

Thresholding Output for Non-blurry Eye

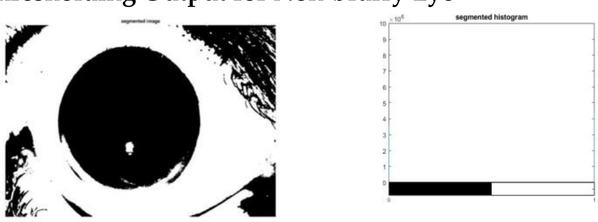

Figure 3.3: Segmented Iris 1 Image and Histogram using Threshold method

Thresholding Code Snippet for Blurry Eye

```
ff= imread ("RECENT.jpeg");
f= imread("noeye1.jpg");
count =0;
T= mean2(f);
done = false;
while (done)
   count =count +1;
   g= f>T;
   Tnext= 0.5*(mean(f(g)))+mean(f(-g));
   done = abs(T-Tnext)<0.5;
   T= Tnext;
end
g= im2bw(f, T/255);
imshow(f), title('Original noeye1 image')
figure, imhist(f), title('Oroginal noeye1 histogram')
figure, imshow(g), title('noeye1 Segmented Image')
figure, imhist(g), title('noeye1 Segmented histogram')
figure, imshow(g), title('noeye1 Segmented Image')
figure, imhist(g), title('noeye1 Segmented histogram')
```

Thresholding Output for Blurry Eye

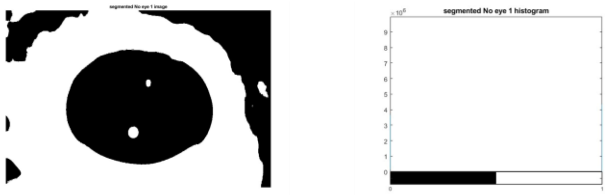

Figure 3.4: Segmented Noeye1 Image and Histogram using Threshold method

The fussion of the thresholding and LPB is done by passing the output of thresholding into the Limbic Pupil Boundary algorithm as input in this study. The pseudocodes and code snippets for the fussion are presented herewith.

Fussion of Thresholding and LPB Pseudocode

Step 1: Start
Step 2: Read the segmented grayscale eye image from a file
Step 3: Convert the image to grayscale.
Step 4: Apply edge detection (Canny edge detection) to extract the iris edges.
Step 5: Find the local maxima points in the edge image.
Step 6: Perform morphological operations (dilation) to enhance and clean up the local maxima points.
Step 7: Overlay the local maxima points on the original image to highlight the segmented iris region.
Step 8: Display the segmented iris image.
Step 9: Stop

Fussion of Thresholding and LPB Code Snippet for Non-blurry Eye

```
% Read the eye image
```


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```
eyeImage = imread('segmented_iris1_image.jpg'); % Replace 'eye_image.jpg' with the path to your eye image
% Convert the image to grayscale
grayImage = rgb2gray(eyeImage);
% Apply edge detection to extract the iris edges
edgeImage = edge(grayImage, 'Canny');
% Find the local maxima points in the edge image
localMaxima = imregionalmax(edgeImage);
% Perform morphological operations to enhance and clean up the local maxima points
se = strel('disk', 5);
localMaxima = imdilate(localMaxima, se);
% Overlay the local maxima points on the original image
segmentedIris = eyeImage;
segmentedIris(repmat(~localMaxima, [1 1 3])) = 0;
% Display the segmented iris image
figure;
subplot(1, 2, 1);
imshow(eyeImage), title('LPB Iris1 Segmented Image');
%imshow(segmentediris);
```

LPB Output for Non-blurry Eye

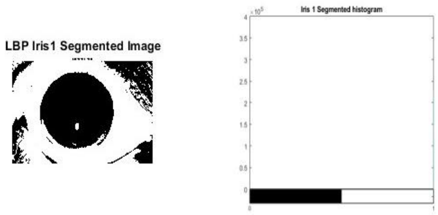

Figure 3.5: Segmented Iris 1 Image and Histogram using Fussed method

3 Result And Discussion

This section presents the result of the study with the graphical representation of the segmented images. The result presentation is done in two parts, the acquired Ayush and CASIA eye image datasets respectively are presented by representation of sample of the acquired data in Figure 4.1 and Figure 4.2. Figure 4.1 is a representation of eye images gotten from Ayush Datasets on Kaggle. The dataset contain a set of 325 non-blurry and 325 blurry eye images a total of 650 eye images. And Figure 4.2 present the eye images gotten from CASIA Dataset. The dataset contain 756 eye images from 80 subjects.

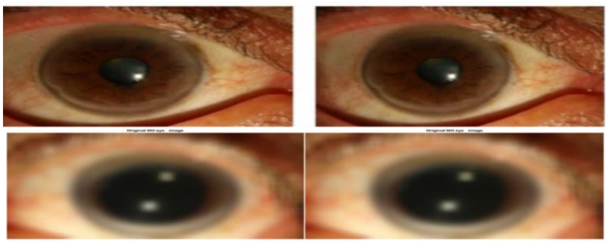

Figure 4.1: Eye Images from Ayush Datasets

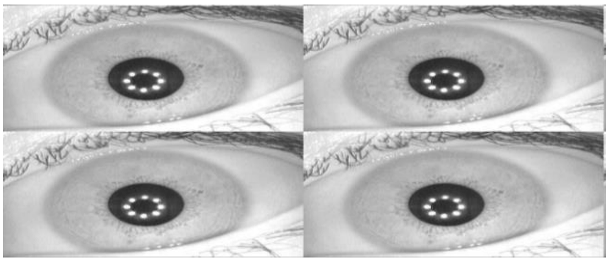

Figure 4.2: Eye Images from CASIA Datasets

After the acquisition of the eye images the next stage in iris recognition system is the iris segmentation and this is done by fussing Thresholding and Limbic Pupillary Boundary methods of segmentation. The result of the segmentation stages are represented in the figures attached herewith. However the acquired images were subjected to preprocessing and their histogram representation were taken before carrying out the segmentation.

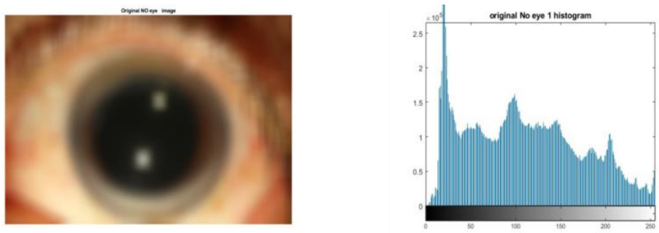

Figure 4.3: Original Iris Image and Corresponding Histogram Representation before Segmentation

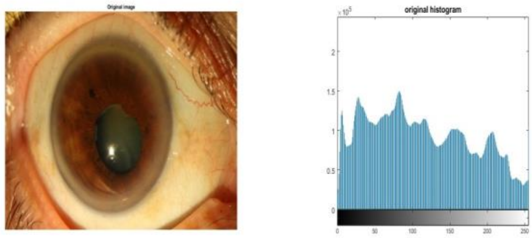

Figure 4.4: Segmented Iris 1 Image and Histogram using Threshold method

The segmentation results were presented in 3 phases; phase 1 has the acquired non-blurry images and their corresponding histogram representation before segmentation and the image of the segmented images with their corresponding histogram representation and phase 2 has the acquired non-blurry images and their corresponding histogram representation before segmentation and the image of the segmented images with their corresponding histogram representation and the phase 3 has the Segmented image using the Fusion method and their histogram representation

A non-blurry (clear) eye image and its histogram representation are shown in Figure 4.3. The histogram displays the region underneath the eye image's

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coordinates in non-binary mode using a threshold range of 0.5 to 2, or the cumulative total of pixel intensities. Since the histogram is displayed in non-binary format, each pixel is given a grayscale value between 0 and 255. This helps in figuring out how the pixel intensities are distributed and how they correspond to the set threshold value, which is then applied to further segment the iris image.

Figure 4.4 shows the thresholded segmented eye image along with its matching histogram representation. This technique divides the image into the iris region and the non-iris region (white and black, respectively) to represent the eye image in binary form. According to the equivalent histogram format, edge detection recognizes regions with values less than 0.5, which are probably caused by noise or occlusion in the image. The thresholding approach achieves an encouraging outcome by demonstrating its abilities as well as efficacy in precisely recognizing and isolating the iris boundary.

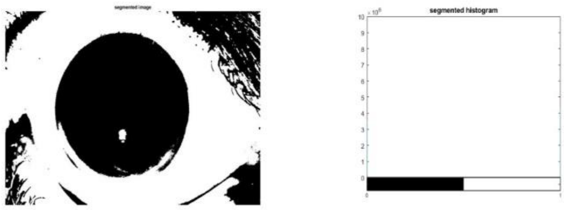

Figure 4.5: Blurry Eye Image and Histogram before Segmentation

Figure 4.5 depicts a blurry eye image with its corresponding histogram representation. The histogram illustrates the intensity distribution beneath the eye's coordinates in a non-binary mode, utilizing grayscale values ranging between 0 and 255, and a threshold value of 0.5 to 2. In contrast to Figure 4.3, the blurry image in Figure 4.5 significantly differs, displaying prominent intensity values that surpass the established threshold. This observation indicates an altered distribution pattern resulting from the blurring effect.

Figure 4.6 illustrates the outcome of thresholding segmentation to the blurry eye image, along with its corresponding histogram representation in a binary format. Similar to Figure 4.4 showcasing the non-blurry image, the segmented image is divided into two regions: the foreground (white) and the background (black). However, in contrast to Figure 4.4, the image edges in Figure 4.5 lack clear definition due to poor image quality, thereby impeding the isolation of distinct iris features. This deficiency in image quality impacts the thresholding technique's ability to accurately isolate the iris boundary.

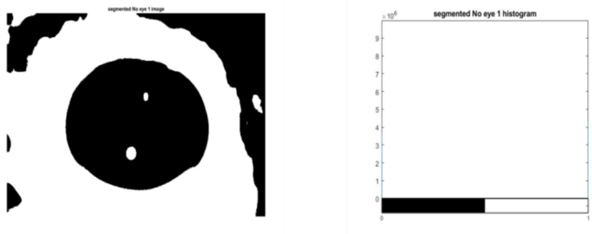

Figure 4.6: Segmented Blurry Eye Image and Histogram using Threshold method

The fusion of the two methods is done by using the segmented image resulted from the thresholding as input for the LPB and a fine edge detection and cutting is gotten as depicted in figure 4.7. In Figure 4.7, the limbic pupil boundary approach yields an impressive result. With an edge detection of roughly 0.5, the histogram representation depicts the intensity distribution of the pixels. This result demonstrates the hybrid method's effectiveness in precisely identifying an iris boundary.

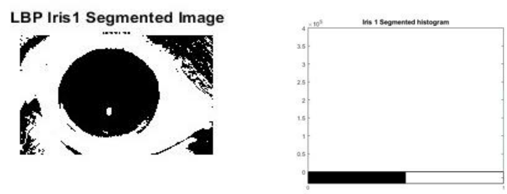

Figure 4.7: Segmented Blurry Eye Image and Histogram using Fusion method

In conclusion, the success of the hybrid approach aids in the overall strength of enhancing the accuracy and robustness of iris segmentation, which play a pivotal role in a reliable and efficient iris recognition system.

4 Conclusion

In conclusion, this project has highlighted the critical role of accurate iris segmentation in AI-based iris recognition systems. By merging Thresholding and Limbic pupil boundary techniques, a novel approach addresses challenges posed by varying image qualities. While the hybrid algorithm demonstrated success in precise segmentation of non-blurry iris regions, the project also uncovered complexities in dealing with blurry images. This fusion-based approach enhances segmentation accuracy, directly impacting the overall performance of recognition systems. This innovation has a significant impact on more reliable and secure biometric identification systems.

References

https://dx.doi.org/10.4314/fuoyejet.v9i1.3 engineering.fuoye.edu.ng/journal

Abikoye, O. C., Afolabi G. K. and, & Aro T. O. (2019). Biometric Based Point of Sale Authentication System. International Journal of Software Engineering and Computer Systems, 5(1), 36–51. https://doi.org/10.15282/ijsecs.5.1.2019.3.0053.

Ahmadi, N., Nilashi, M., Samad, S., Rashid, T. A., & Ahmadi, H. (2019). An intelligent method for iris recognition using supervised machine learning techniques. Optics and Laser Technology, 120(December 2018), 105701. https://doi.org/10.1016/j.optlastec.2019.105701.

Akande, O., Ojimba, N., Oghenekaro, A., Abikoye, O., Ogundokun, R., & Akindele, A. (2022). AFHIRIS: African Human Iris Dataset (Version 1). F1000Research, 11(Version 1), 1549. https://doi.org/10.12688/f1000research.122759.1.

Buddharpawar, A. S., & Subbaraman, S. (2015). Iris Recognition based on PCA for Person Identification. International Journal of Computer Applications Signal Processing and Computing Technologies, 2(Ncesc), 975–8887.

K. Singla, R. Namboodiri, P. Verma and R. A. Shaikh (2019), "A Novel Approach for Iris Localization using Machine Learning Algorithms," 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), Dubai, United Arab Emirates, 2019, pp. 50-55, doi: 10.1109/ICCIKE47802.2019.9004263.

K., S., T., C., & M., C. D. (2015). Iris Recognition Based on Kernels of Support Vector Machines. ICTACT Journal on Soft Computing, 05(02), 889–895. https://doi.org/10.21917/ijsc.2015.0125.

Khuzani, A. Z., Mashhadi, N., Heidari, M., & Khaledyan, D. (2020). An approach to human iris recognition using quantitative analysis of image features and machine learning. 2020 IEEE Global Humanitarian Technology Conference, GHTC 2020. https://doi.org/10.1109/GHTC46280.2020.9342935

Malgheet, J. R., Manshor, N. B., Affendey, L. S., & Halin, A. B. A. (2023). MS-Net: Multi-Segmentation Network for the Iris Region using Deep Learning in an Unconstrained Environment. IEEE Access, 11, 59368-59385. https://doi.org/10.1109/ACCESS.2023.3282547

Nirgude, M., & Gengaje, S. (2017). Iris Recognition System based on Multi-resolution Analysis and Support Vector Machine. International Journal of Computer Applications, 173(7), 28–33. https://doi.org/10.5120/ijca2017915366.

Ohmaid, H., Eddarouich, S., Bourouhou, A., & Timouyas, M. (2020). Comparison between and classifiers for iris recognition using a new unsupervised neural approach in segmentation. IAES International Journal of Artificial Intelligence, 9(3), 429–438. https://doi.org/10.11591/ijai.v9.i3.pp429-438.

Reyes-Lopez, J., Campos, S., Allende, H., & Salas, R. (2012). Zernike's feature descriptors for iris recognition with SVM. Proceedings - International Conference of the Chilean Computer Science Society, SCCC, 283–288. https://doi.org/10.1109/SCCC.2011.36,

Sarhan, A. M. (2009). Iris recognition using discrete cosine transform and artificial neural networks. Journal of Computer Science, 5(5), 369–373. https://doi.org/10.3844/jcssp.2009.369.373

Shao, S., & Xie, M. (2006). Kernel-based classifier for iris recognition. International Conference on Signal Processing Proceedings, ICSP, 4(3), 0–3. https://doi.org/10.1109/ICOSP.2006.345932

Shelke, R., & Bagal, S. B. (2018). Iris Recognition System: A Novel Approach for Biometric Authentication. 2017 International Conference on Computing, Communication, Control and Automation, ICCUBEA 2017, 1–5. https://doi.org/10.1109/ICCUBEA.2017.8463819

Shrivas, A., & Tuli, P. (2012). Effective analysis of Iris Images for Iris Recognition System. International Journal of Science and Engineering Applications, 1(1), 85–88. https://doi.org/10.7753/ijsea0101.1015

Vasavi, J., & Abirami, M. (2020). A Qualitative Performance Comparison of Supervised Machine Learning Algorithms For Iris Recognition. European Journal of Molecular & Clinical Medicine, 07(06), 2020.

Wang, Y., & Han, J. Q. (2005). Iris recognition using independent component analysis. 2005 International Conference on Machine Learning and Cybernetics, ICMLC 2005, 1(August), 4487–4492. https://doi.org/10.1109/icmlc.2005.1527729

Yung-Hui Li, Po-Jen Huang, Yun Juan, "An Efficient and Robust Iris Segmentation Algorithm Using Deep Learning", Mobile Information Systems, vol. 2019, Article ID 4568929, 14 pages, 2019. https://doi.org/10.1155/2019/4568929

Zhang, P. F., Li, D. S., & Wang, Q. (2004). A novel iris recognition method based on feature fusion. Proceedings of 2004 International Conference on Machine Learning and Cybernetics, 6(August), 3661–3665. https://doi.org/10.1109/icmlc.2004.1380440.