An approach to human iris recognition using quantitative analysis of image features and machine learning

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Abstract—The Iris pattern is a unique biological feature for each individual, making it a valuable and powerful tool for human identification. In this paper, an efficient framework for iris recognition is proposed in four steps. (1) Iris segmentation (using a relative total variation combined with Coarse Iris Localization), (2) feature extraction (using Shape&density, FFT, GLCM, GLDM, and Wavelet), (3) feature reduction (employing Kernel-PCA) and (4) classification (applying multi-layer neural network) to classify 2000 iris images of CASIA-Iris-Interval dataset obtained from 200 volunteers. The results confirm that the proposed scheme can provide a reliable prediction with an accuracy of up to 99.64%.

Keywords: Iris, image processing, segmentation, feature extraction, FFT, Wavelet, GLCM, GLDM, Kernel-PCA, Multi-layer neural network.

I. INTRODUCTION

The iris is a part of the eye that controls the pupil's size, regulating the amount of light that enters the eye. It is the part of the eye with coloring based on the amount of melatonin pigment within the muscle.

The individual's irises patterns are unique and structurally distinct, which remains stable throughout adult life and makes it suitable to be used for reliable automatic recognition of persons as an attractive goal. Iris recognition is employed as the most reliable and accurate biometric identification system, compared with other biometric technologies, such as speech, finger, and face recognition [1-4].

Automated iris segmentation has been an attractive topic of research in the recent past [5, 6], and many methods [7-9] have been proposed to solve the problem. The first automatic method was presented by Daugman [10] using an efficient integrodifferential operator, which is still utilized in today's most of the iris recognition systems. Image processing techniques as the first step can be applied to extract the unique pattern from the image, and encode it [11-20]. The feature extraction is another important part of Iris recognition discussed in some researches [3, 7, 10]. The shape and texture features are useful for identifying the Iris region's geometric properties. In contrast, FFT and Wavelet feature mostly represent energy distributions and convergence at different frequencies and boundaries, making them helpful in quantifying the Iris region heterogeneity [21-24]. Also, GLDM and GLCM features are useful for identifying and computing the textures for assessing the heterogeneity in Iris region textual details [25-29].

In this paper, we proposed a four-stage machine learning-based Iris recognition using eye images. In the first step, we implemented the Iris region segmentation function by applying two techniques of relative total variation and Coarse Iris Localization, improved by shearlet transform in the edge detection stage. We also used Daugman's rubber sheet model to transfer the detected Iris region to a rectangular form. In the second step, we proposed a computation and analysis scheme to generate a feature pool of spatial and frequency components from each segmented Iris region. In the third step, we reduced the feature pool size to find the optimal feature fusion and remove less important features by employing the Kernel-PCA technique. The final feature vector was fed to a multi-layer neural network, proposed in the fourth step.

II. MATERIALS AND METHODS

A. Dataset

The proposed approach's performance was evaluated on available databases CASIA-Iris-Interval version 4 under near-infrared, including 100 people and ten eye images per person, 2000 images in total [30]. One close-up iris camera is used to capture Iris images of this dataset. The camera, used in this dataset, employs a circular NIR LED array, with suitable luminous flux for the imaging. Because of this novel design, the iris camera can capture very clear iris images (Fig.1). CASIA-Iris-Interval is well-suited for analyzing the detailed texture features of iris images.

B. Iris Region Segmentation

The preprocessing part consisted of enhancement, noise removal, and reflection removal. Some factors, including angle
and intensity of illumination source, can leave an undesirable effect on the quality of iris image and, as a result, on segmentation and recognition accuracy. To address this problem, the Single Scale Retinex (SSR) method and normalizing eye image illumination are proposed in [31].

After enhancement, we applied a median filter to the iris image to remove isolated noisy pixels(Fig. 2b). Then we removed undesired reflection, which occurs under a less-constrained imaging environment, by a thresholding process so that pixels whose gray levels are higher than the highest threshold were moderated (Fig. 2c).

![Fig. 1: An example of iris images in the CASIA-Iris-Interval dataset.](image)

![Fig. 2: Preprocessing of a single eye image. a) Original image. b) Enhanced version. c) Reflection removal.](image)

To identify iris boundaries and separate it from other parts like the pupil, and eyelids, we used an approach proposed in [32]. This segmentation method, employing relative total variation and Coarse Iris Localization techniques, is able to segment the iris area in the target eye image effectively. However, it utilizes conventional edge detection techniques such as Canny and Sobel to find edges in the image. We replaced the edge detection function with a more accurate edge detection approach (Fig. 3) employing shearlet transforms [33].

![Fig. 3: The edge detection method based on shearlet transforms.](image)

![Fig. 4: Edge detection results. a) Proposed method. b) Canny method. c) Sobel method](image)

![Fig. 5: Iris segmentation process. a) Preprocessed image. b) Iris and pupil circle localization. c) Extracted iris area d) Eyelids removal.](image)

Fig. 4 confirms that the proposed method localizes the distributed discontinuities in binary eye images more efficiently compared with Canny and Sobel methods. Also, Fig. 5 summarizes the steps of our Iris segmentation process that we applied to separate the Iris region from other parts of the eye image.

After segmentation, we transferred each angular segmented region to a rectangular mapped image with the fixed size for all cases using Daugman’s rubber sheet model (Fig. 5 and Fig. 6), where radius r is between 0 and 1, and θ is 1 to 360 degree.

C. Feature extraction

In this step, we used a scheme to extract 252 features from both the spatial and frequency domains including shape&density, Gray Level Difference Method (GLDM), Gray-Level Co-Occurrence Matrix (GLCM) method, Fast Fourier Transform (FFT), and Wavelet transform (Fig. 8 and Fig. 9). For each group and each subsection, we measured 14 features applying the same statistical calculations such as Area, Mean, Std, Max, Min, Mean Deviation, Energy, Entropy, Kurtosis, Skewness, Range, RMS, Median, and Uniformity resulting in 252 features for each iris region totally. We performed GLCM and GLDM techniques in four different directions, and Wavelet transforms were also implemented in eight sub-bands.
**D. Feature reduction**

Given the initial pool of 252 features, we used the Kernel-PCA technique to discard non-useful features and find an optimal feature fusion. By engaging the PCA technique performed in a kernel Hilbert space, and then select the most important features [34], the original feature pool was converted to 100 new synthetic features (Fig. 10). We finally applied this new optimal feature vector in the classification and recognition step.

**E. Machine learning-based classifier**

For the classification and recognition task, we implemented a multi-layer neural network (Fig. 10) using Keras library in python. Nowadays, neural networks and deep learning models are important parts of detection, prediction, classification, and recognition systems with different applications [35-41]. Our designed model was built by applying two hidden layers (with 1000 and 400 neurons, respectively) followed by one output classifier with 200 output class labels matching to 200 people in our dataset. Also, we used drop-out techniques to decrease the risk of overfitting during the training process. The total number of pf parameters in this neural network model is 581,600, which is effectively lower than deep learning models usually used in classification and recognition tasks such as AlexNet, Vgg, GoogleNet, and ResNet.

**III. RESULTS**

**A. Analysis of extracted features**

Fig. 11a shows the Pearson correlation coefficient matrix of the original extracted 252 features for 2000 observations. This map reveals that the Wavelet group has less dependence compared to other groups. Also, the histogram of correlation coefficients is shown in Fig. 11b indicates that the feature pool generated in our study can provide a comprehensive representation of the iris region because more than 80% of the correlation coefficient values were less than 0.5.

We used the AUC value (Area under the ROC curve) as an indicator to compare the discrimination power of different single (e.g., RMS, mean_wavelet, std_GLDM) and group (e.g.,
Shape&Density, FFT, GLCM) features shown in Fig. 12. We sorted all the features in the order of their average AUC value (Fig. 12a). As seen, most of the features (148 out of 252) showed the AUC value of more than 0.6, while Entropy, Mean FFT, and Energy Wavelet are the top three features with an AUC value of 0.88±0.06, 0.86±0.07, 0.84±0.08, respectively. Also, the FFT group recorded the best performance among the other features groups confirming the importance of frequency features compared to spatial features. In contrast, the lowest performance belonged to the GLCM group (Fig. 12b).

B. Performance of Kernel-PCA features and neural network classifier

To train our proposed neural network classifier, we employed Adam optimizer to minimize categorical cross-entropy loss function during the training process. The other hyperparameters we set included MaxEpochs=100, BatchSize=8, LearningRate=0.0001, DropoutValue=0.2, ValRatio=0.2, TrainRatio=0.6, and TestRatio=0.2. Fig. 13 shows the performance of the training process comparing validation and training loss function values converged at 35 epochs with a score value of 0.24 and the accuracy of 97.6% for the test set.

Table 1 shows the average performance of our proposed iris recognition scheme confirming that the synthetic optimal feature group (K-PCA features) achieves a considerably better performance than the best single feature in Fig. 12a.

Fig. 12: The comparison of the discrimination power of the extracted features. a) AUC values of single features sorted. b) Average AUC values of different groups.

Table 1 shows the average performance of our proposed iris recognition scheme confirming that the synthetic optimal feature group (K-PCA features) achieves a considerably better performance than the best single feature in Fig. 12a.

| Precision | Sensitivity | F-score | Support |
|-----------|-------------|---------|---------|
| 0.97      | 0.95        | 0.96    | 400     |

Fig. 13: Loss score graph of the training process for designed machine learning classifier

IV. CONCLUSION AND DISCUSSION

In this study, we showed that our proposed machine learning scheme of iris region segmentation, feature extraction, and neural network classifier could accurately recognize and classify Iris images. Unlike various previously proposed machine learning schemes that use the texture-based features in the spatial domain, we computed image features in both the spatial and frequency domains. Also, since creating optimal and most effective image features is one of the most critical tasks in building machine learning-based classifiers, we investigated the importance of utilizing a data reduction method to select more correlated and optimal features. The results proved that our feature reduction method decreases the size of feature space and can replace the new smaller feature vector with more correlated information and a lower redundancy.

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