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Iris Recognition Based on Multilevel Thresholding Technique and Modified Fuzzy c-Means Algorithm

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Abstract: Biometrics represents the technology for measuring the characteristics of the human body. Biometric authentication currently allows for secure, easy, and fast access by recognizing a person based on facial, voice, and fingerprint traits. Iris authentication is one of the essential biometric methods for identifying a person. This authentication type has become popular in research and practical applications. Unlike the face and hands, the iris is an internal organ, protected and therefore less likely to be damaged. However, the number of helpful information collected from the iris is much greater than the other biometric human organs. This work proposes a new iris identification model based on a multilevel thresholding technique and modified Fuzzy c-means algorithm. The multilevel thresholding technique extracts the iris from its surroundings, such as specular reflections, eyelashes, pupils, and sclera. On the other hand, the modified Fuzzy c-means is used to combine and classify the most useful statistical features to maximize the accuracy of the collected information. Therefore, having the most optimal iris recognition. The proposed model results are validated using True Success Rate (TSR) and compared to other existing models. The results show how effective the combination of the two stages of the proposed model is: the Otsu method and modified Fuzzy c-means for the 400 tested images representing 40 people.

Keywords: Biometric authentication; recognition; iris recognition; statistical features; feature extraction; fuzzy c-means; TSR; sensitivity; classification

1 Introduction

The process of validating a person's identity based on his/her characteristics is called authentication. Several identification methods are proposed for implementing a trade-off between technological solutions and safety-related information [1–3].

Biometrics is considered the most accurate and reliable technology to authenticate and identify a person based on his/her biological characteristics, such as hand morphology, retina, iris, voice, DNA fingerprints, and signatures [4].

Iris is one of the safest and most accurate biometric authentication methods. Unlike the hands and face, the iris is an internal organ, protected and therefore less likely to be damaged [5–7].

The authors in [8] have proposed a new model for iris recognition using the Scale Invariant Feature Transformation (SIFT). First, the SIFT characteristic feature is extracted. Then, the matching process is performed between two images. This matching is achieved based on associated descriptors by comparing each local extrema. Experiments results using the BioSec multimodal database demonstrate that the combination of the SIFT with a matching approach achieves significantly better performance than more existing approaches.

Another model is the Speeded Up Robust Features (SURF), proposed in [9]. This model extracts unique features from annular iris images, which results in satisfactory recognition rates. In [10], the authers developed a system for iris recognition using a SURF key that is extracted from normalization and enhancing images of the iris. This process will provide high accuracy.

With the same objective, Masek [11] has taken advantage of the Canny edge detector and the circular Hough transform to detect iris boundaries. The Log-Gabor wavelets extract features and apply Hamming distance for recognition. In [12], the authors developed an iris recognition system that characterizes local variations of image structures. This work builds a one-dimensional (1D) intensity signal with essential local variations of the original 2D iris image. Moreover, intensity signals Gaussian–Hermite moments are utilized as distinguishing features. For classification, the cosine similarity measure and nearest center classifier are used.

Some recent papers have used machine learning for iris recognition. For example, in [13], the authors' framework proposes a model that uses artificial neural networks or personal identification. Another paper [14] uses neural networks for iris recognition. This paper extracts the eye from an image and then normalizes and enhances it. This process is applied to many images that are collected in one dataset. The neural network is employed on this dataset for iris classification.

In our proposed model, the iris recognition system includes two main stages: "Iris segmentation and localization" and "Feature classification and extraction" [15]. Fig. 2 shows the steps of the methodology and the sequential proposed iris recognition system processing.

The face recognition method in this work has a different concept and explores a new strategy. The notion behind the proposed model is to explore all possible solutions for merging the multilevel thresholding method and Fuzzy c-means algorithm instead of elaborating a better-designed iris recognition model.

In the first step, some image processing solutions are utilized for pulling the iris from the image. Once the iris is localized, the two-stage multi-threshold Otsu's technique segments the iris into two classes. Eventually, feature extraction is employed using a statistical features technique, and the FCM classifier is used for classification.

Section 2 discusses the proposed iris recognition model. The results are represented in Section 3. Section 4 concludes the paper.

2 The Proposed Method

Iris recognition is a biometrics technique that recognizes a person based on their iris. It represents an automated method that allows to authenticate/identify a person using the iris features. Practically, iris recognition can be carried out images (photos) or video recordings of one or both irises of an individual's eyes using mathematical pattern recognition techniques, including complex patterns are unique, stable and can be seen from some distance.

In this work, we are interested in identifying people by their iris. The proposed system is conceptually different and explores new strategies. Indeed, rather than considering refinement of a better-designed iris recognition model, the proposed method suggests a possible alternative of combining a multi-level thresholding technique with a modified fuzzy c-means algorithm.

The proposed iris recognition method is developed using four fundamental steps: (1) Localization, (2) segmentation, (3) encoding, and (4) iris matching/classification [15].

The iris localization step consists of detecting the iris in the human image. The second step is to segment the images into two classes, iris, and non-iris. The main phase of the recognition cycle is the feature extraction which consists of extracting the feature vector for each iris identified in the second phase. Extracting the features accurately leads to an accurate output for the next steps. The features of the iris are extracted from raw images, a feature vector is built based on the statistical feature technique, and finally, the iris recognition result is obtained using the modified FCM technique. In the recognition phase, matching and classification of image features can be performed concerning specific criteria to specify the identity of an iris compared to all template iris databases. The flowchart shown in Fig. 1 depicts the stages of the proposed method.

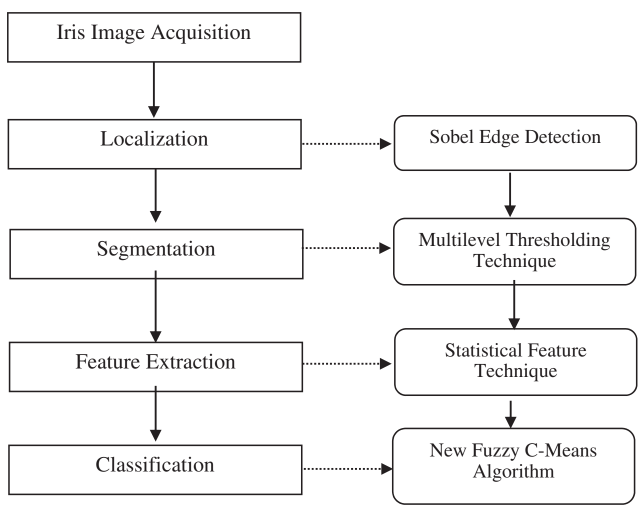
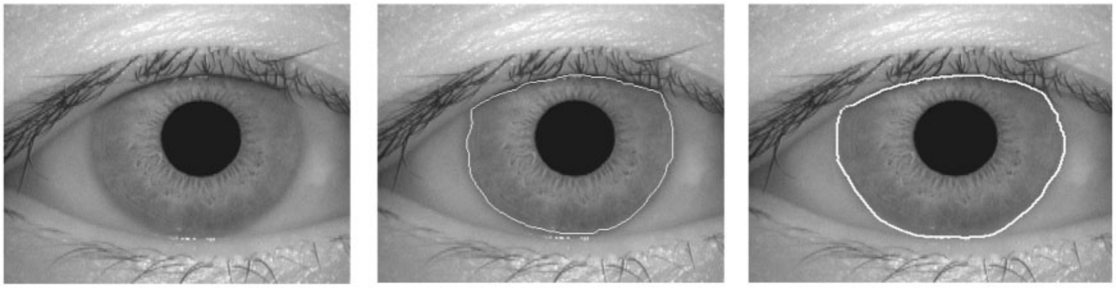


Figure 1: The diagram of the proposed method



(a) (b) (c)

Figure 2: The localization of iris. (a) Original image, (b) Edge detection using sobel filter, (c) Reference result

2.1 Iris Localization

Iris localization is one of the most important steps in an iris recognition system that determines match accuracy. This step mainly identifies the border of the iris. The iris border is the inner and outer border of the iris and the upper and lower eyelids. To do this, Sobel edge detection can be used to locate the iris in the original image. Sobel edge detection is based on image convolution with two integer filters, one horizontal and one vertical. This filter starts with the edge with the highest slope. Fig. 2 presents the localization of the iris using the Sobel edge detection and the reference edge detection.

2.2 Multilevel Thresholding Using a Two Stage Optimization Approach

In order to select the optimal thresholds for both unimodal and bimodal distributions, and to greatly improve the shortcomings of Otsu's method in terms of multistage threshold selection, we used Two-stage Multithreshold Otsu's method [16]. The general concept of the TSMO method is presented in reference [16].

Using this technique can significantly reduce the iterations required to compute the zeroth and first order moments of the class. In order to automatically classify the eyes image into the predefined categories of eyes and noneyes, we developed the two-stage thresholding technique.

At the first stage, the histogram of an image with L gray levels is divided into Mk groups which contain Nk gray levels.

Let $\Omega = \{\Omega_j \backslash j = 0, 1, 2, \ldots M_k - 1\}$ denotes the groups of the total image space, where j represents the group number. Each group contains a range of gray levels as follows:

$$\begin{cases} \Omega_0 = \{0,\ \ 1,\ \ 2,\ \ \ldots,\ \ N_k - 1\} \\ \Omega_1 = \{N_k,\ \ N_k + 1,\ \ \ldots,\ \ 2N_k - 1\} \\ \qquad\qquad\qquad\qquad \ldots \\ \qquad\qquad\qquad\qquad \ldots \\ \Omega_q = \{qN_k,\ \ qN_k + 1,\ \ \ldots,\ \ (q+1)\,N_k - 1\} \\ \qquad\qquad\qquad\qquad \ldots \\ \Omega_{M_k-1} = \{(M_k - 1)\,N_k,\ \ (M_k - 1)\,N_k + 1,\ \ \ldots,\ \ M_kN_k - 1\} \end{cases} \tag{1}$$

The zeroth-order cumulative moment in the qth group denoted by G_{Ω_q} which represents the number of cumulative pixels, can be calculated as:

$$G_{\Omega_q} = \sum_{i=q\times N_k}^{(q+1)\times N_k - 1} f_i \tag{2}$$

where: f_i represents the number of pixels with gray level i.

The first-order cumulative moment in the qth group denoted by i_{Ω_q} can be calculated as:

$$i_{\Omega_q} = \frac{\sum_{i=q\times N_k}^{(q+1)\times N_k - 1} i.f_i}{\sum_{i=q\times N_k}^{(q+1)\times N_k - 1} f_i} \tag{3}$$

The optimal threshold j^* is taken as the number of the group into which the between-class variance σ_B^2 is maximal. The optimal threshold j^* is defined as:

$$j^* = argmax_{0\le j\le M_k - 1}\left(\sigma_B^2\,(j)\right) \tag{4}$$

However, the image is divided into two classes C_1 and C_2 (eye, non-eye) by Ω_{j^*}, where the class C_1 consists of the group from Ω_0 to Ω_{j^*} and the class C_2 contains the other groups with Ω_{j^*+1} to Ω_{M_k-1}.

The numbers of the cumulative pixels (W_1, W_2) and the means (μ_1, μ_2) for the two classes (C_1, C_2), respectively, are given by:

$$W_1\,(j^*) = \sum_{j=0}^{j^*} G_{\Omega_j} \tag{5}$$

$$W_2\,(j^*) = \sum_{j=j^*+1}^{M_k-1} G_{\Omega_j} \tag{6}$$

and

$$\mu_1 = \frac{\sum_{j=0}^{j^*} i_{\Omega_j}.G_{\Omega_j}}{W_1} \tag{7}$$

$$\mu_2 = \frac{\sum_{j=j^*+1}^{M_k-1} i_{\Omega_j}.G_{\Omega_j}}{W_2} \tag{8}$$

In the case of bi-level thresholding ($M = 2$), the maximum variance of the between-class is defined as:

$$\left(\sigma_B^2\right)_{max} = \sum_{k=1}^{M} W_k\mu_k^2 = W_1\mu_1^2 + W_2\mu_2^2 \tag{9}$$

At the second stage of multilevel thresholding technique, in order to find the optimal threshold T, Otsu's method is applied again to the group Ω_{j^*} with gray levels $\{j^*N_k,\ j^*N_k + 1, \ldots,\ (j^* + 1)\,N_k - 1\}$ in which $\left((\sigma_B^2)'j^*\right)$ has already been found at the first stage.

The optimal threshold T is defined as:

$$T = argmax_{j^*N_k\le t\le\left(j^*+1\right)N_k-1}\left((\sigma_B^2)'\,(t)\right) \tag{10}$$

Given the optimal threshold determined automatically by the two-stage Otsu optimization approach, the I_T function classifies the pixels of the input image into two opposite classes (object and background) as follows:

$$I_T(x,y) = \begin{cases} 1\ interrest\ object & I(x,y) \geq T \\ 0\ background & I(x,y) < T \end{cases} \tag{11}$$

2.3 Feature Extraction

During feature extraction, the system extracts the features from the segmented image [17]. To do this, the statistical method is used to complete the best statistical features and to build the attribute images [18]. The importance of feature extraction comes from that it determines the overall system performance. Usually, face recognition systems start with feature extraction, then feature selection, which increases the framework accuracy. The feature selection is a must since it affects the overall performance of the recognition system.

This work presents a new iris recognition technique that relies on statistical features. These features are commonly utilized in data science. It is usually the first statistical technique when examining a dataset, and it has various statistical properties such as skewness, variance, mean and median.

In our preprocessing stage, four statistical characteristics have been selected like mean, standard deviation, skewness, and kurtosis to ensure the distinctiveness and variations of features with application to iris recognition system.

Instead of using the grayscale value of a particular pixel in the human iris median step, statistical features are computed from a sliding window (W_{xy}) centered around each pixel (p_{xy}) in the original image. Suppose g_{xy} is the intensity of a pixel p_{xy} at the location (x, y) in the $(m \times n)$ image, then (W_{xy}) is a window of size $(p \times p)$ centered at (x, y) for the computation of statistical features. The adaptive sliding window shown in Fig. 3 runs left-to-right and top-to-bottom.

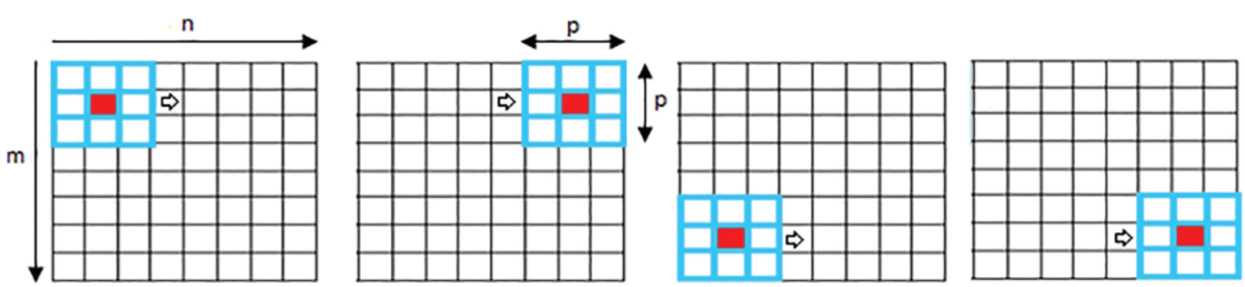


Figure 3: The adaptive sliding window

The statistical attributes used in our application, as shown in Fig. 4, are: mean (Me), variance (Var), skewness ($Skew$), and kurtosis (Kur) which are given for an image I of size $(m \times n)$ by the following equations:

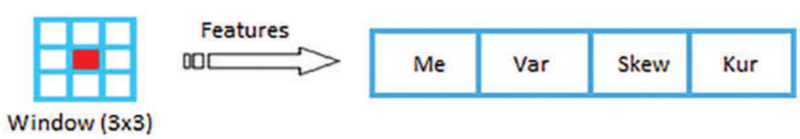


Figure 4: The features extraction

$$Me(x,y) = \frac{1}{p \times p} \sum_{i=x-\frac{p-1}{2}}^{x+\frac{p-1}{2}} \sum_{j=y-\frac{p-1}{2}}^{y+\frac{p-1}{2}} I(i,j) \tag{12}$$

$$Var(x,y) = \frac{1}{p \times p} \sum_{i=x-\frac{p-1}{2}}^{x+\frac{p-1}{2}} \sum_{j=y-\frac{p-1}{2}}^{y+\frac{p-1}{2}} \left(I(i,j) - Me(x,y)\right)^2 \tag{13}$$

$$Skew(x,y) = \frac{1}{p \times p} \sum_{i=x-\frac{p-1}{2}}^{x+\frac{p-1}{2}} \sum_{j=y-\frac{p-1}{2}}^{y+\frac{p-1}{2}} \left(I(i,j) - Me(x,y)\right)^3 \tag{14}$$

$$Kur(x,y) = \frac{1}{p \times p} \sum_{i=x-\frac{p-1}{2}}^{x+\frac{p-1}{2}} \sum_{j=y-\frac{p-1}{2}}^{y+\frac{p-1}{2}} \left(I(i,j) - Me(x,y)\right)^4 \tag{15}$$

The calculation of the statistical features is affected by the length of the sliding window, hence, it is important for the window to provide ample space to capture sufficient information from the raw image. In contrast, if the window length is excessively long, this can be considered time-consuming. A (3×3) window is empirically chosen to weigh the strengths and weaknesses and calculate the statistical features.

2.4 Use of Modified Fuzzy C-Means for Classification

A similarity measure is presented based on the previously extracted features to find the contrast between two irises. There are many techniques used to compare irises. References include distance calculations and similarity calculations. Other methods are based on classifying features using a single classifier such as SVM, Bayes classifier, etc.

Optimal Iris Feature Descriptors and Fuzzy C-Means seem to be an intriguing approach for iris recognition in this context. Moreover, we suggest substituting the pixel-value-based technique with a vector F that comprises the most effective statistical features to enhance the iris recognition accuracy.

The proposed image segmentation technique using the FCM algorithm combined with the statistical features can be summarized by the following steps:

Step 1: Initialization (Iteration $t = 0$)

Randomly initialize the matrix $V(0)$ of size $(c \times 4)$ containing the centers of the classes.

Step 2: Construction of the matrix F of size $(d \times 4)$ containing the statistical features extracted from the original image as detailed in the last paragraph.

From the iteration $t = 1$ to the end of the algorithm:

Step 3: Calculate the membership matrix $U^{(t)}$ of element u_{ik} using:

$$u_{ik} = \frac{1}{\sum_{i=1}^{c} \left(\frac{||F_k - v_i||}{||F_k - v_j||}\right)^{\frac{2}{m-1}}}$$

where, F_k and v_i are vectors of size (1 × 4.

Step 4: Calculate the matrix $V^{(t)}$ composed of 4 columns v_i using:

(Continued)

(Continued)

$$v_i = \frac{\sum_{k=1}^{d} u_{ik}^m F_k}{\sum_{k=1}^{d} u_{ik}^m}$$

Step 5: Convergence test: if $\left|\left|V^{(t)} - V^{(t-1)}\right|\right| < \varepsilon$, then increment the iteration t, and return to the Step 3, otherwise, stop the algorithm. ε is a chosen positive threshold

So, the steps of the proposed iris recognition technique using multi-level thresholding technique combined with Modified Fuzzy C-means algorithm are presented in Algorithm 1.

Algorithm 1: Iris recognition using Modified Fuzzy C-means algorithm combined with multi-level thresholding technique.

Input: Face images from ORL Output: Face image recognition
Step 1: A Face database has been generated, containing face images with a dimension of 92 $\times$ 112.
Step 2: The two-stage Otsu optimization approach is used to select the iris in the human image of size 92 $\times$ 112.
Step 3: Use the Statistical Features to generate final set of features.
Step 4: Using a modified fuzzy c-means algorithm, the features of the test image are compared with those of the database image.

3 Experimental Results and Discussion

To evaluate the efficiency and accuracy of the proposed method, the results are compared *vs.* existing methods, as described earlier. The experiments are carried out on the MATLAB software 10.

The images originally are stored in gray level format and uses 8 bits with integer values between 0 and 255. Performance analysis considers the CASIA Iris database. This database contains 756 images from 108 different individuals. This database is currently the largest publicly available Iris database.

After performing the image segmentation described in Section 3.1, the homogeneous regions of each image were obtained. The original multilevel thresholding algorithm is used to address known number of regions in an image (iris and pupil) for image segmentation.

Fig. 5 shows the segmentation results for one example image. In this figure, (a) is an example image in the database and (d) is its region representation. Each segmented region is characterized by the average gray level of all pixels associated with that region. The segmentation results show that the two regions were correctly segmented by optimal multi-level thresholding using the two-level Otsu optimization approach. Accuracy evaluation uses a segmentation sensitivity criterion to determine the number of correctly classified pixels. Iris images evaluated on 756 images from the CASIA database were used. Some sample images are shown in Fig. 6. Image segmentation of the test database took 5.5 h and took about 1.9 s per image.

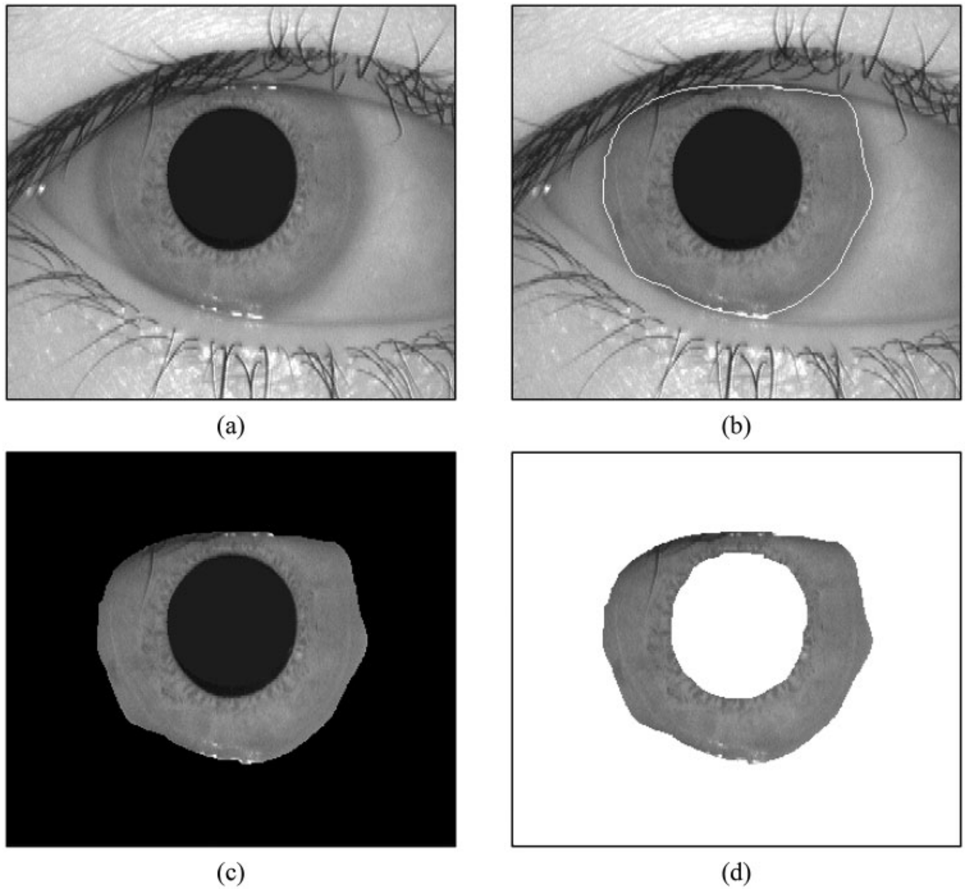


Figure 5: Image segmentation. (a) Original image. (b) Iris localization. (c) Segmented image (3 regions: Iris, Pupil, and background). (d) Segmented image (2 regions: Iris and background)

The segmentation sensitivity of some existing methods FAMT [19], FSRA [20], BWOA [21] and the two-stage Otsu optimization approach (TSOM) [22] is shown in Table 1. It can be seen from Table 1 that 31.77%, 20.44%, and 2.73% of pixels were incorrectly segmented by FAMT [19], FSRA [20], BWOA [21] and the two-stage Otsu optimization approach [22], respectively. In fact, the experimental results indicate that the multilevel thresholding technique is more accurate than existing methods in terms of segmentation quality, and the two regions are correctly segmented by the optimal multi-level thresholding using a two-stage Otsu optimization approach.

We calculated the segmentation sensitivity as follows:

$$Sen\,(\%) = \frac{Npcc}{M \times N} \times 100 \tag{16}$$

where:

$Npcc$: is the number of correctly classified pixels.

$M \times N$: is the size of image.

The overall analysis performed in this study randomly split the 756 images into training and test datasets.

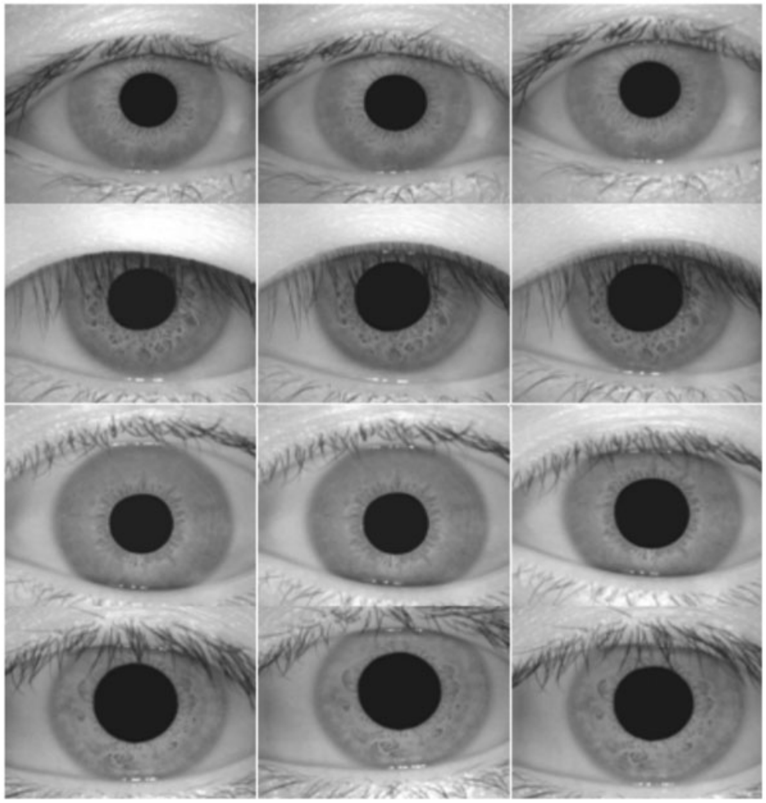


Figure 6: Example of irises of the human eye. Twelve were selected for a comparison study. The patterns are numbered from 1 through 12, starting at the upper left-hand corner. Image is from CASIA iris database (Fernando Alonso-Fernandez, 2009)

Table 1: Segmentation sensitivity from FAMT [19], FSRA [20], BWOA [21] and TSOM [22] for the data set shown in Fig. 6

	FAMT	FSRA	BWOA	TSOM
Image 1	97.6642	96.7067	97.7610	98.6409
Image 2	96.6461	95.6986	96.7419	97.6126
Image 3	97.7018	96.7440	97.7987	98.6789
Image 4	98.2627	97.2994	98.3601	99. 2454
Image 5	95.7377	94.7991	95.8326	96.6951
Image 6	96.6490	95.7014	96.7447	97.6155
Image 7	96.5125	96.0371	96.6082	97.4777
Image 8	97.7358	97.2543	97.8327	98.7132
Image 9	98.6629	98.1769	97.7915	99.6496
Image 10	95.5424	95.0718	94.6986	96.4979
Image 11	95.6187	95.1476	94.7741	96.5749
Image 12	96.6222	96.1463	95.7688	97.5885

Datasets are often separated into training and testing datasets in a 4:3 ratio. Therefore, 432 images are randomly selected as training set and 324 are selected from all cases as test images. A total of four iris images for each subject are selected as the training set for the feature extraction method. The training set contains 108, 216, 324, and 432 images, depending on the number of images selected. For each person, irises with the same index are selected for the corresponding set.

In the way to reduce the dimensions of the training set, some statistical features are selected randomly, and M feature vectors that correspond to them are used to form a training set with a smaller size. This process would help reduce the number of operations the $MFCM$ classifier needed.

For a more straightforward and achievable classification process, we utilize only ($M = 80, 120, 160$) feature vectors randomly selected for $MFCM$ and nearest distance classification.

It is evident from Fig. 7 and Table 2, that an increase in the number of training images results in an enhancement of recognition accuracy.

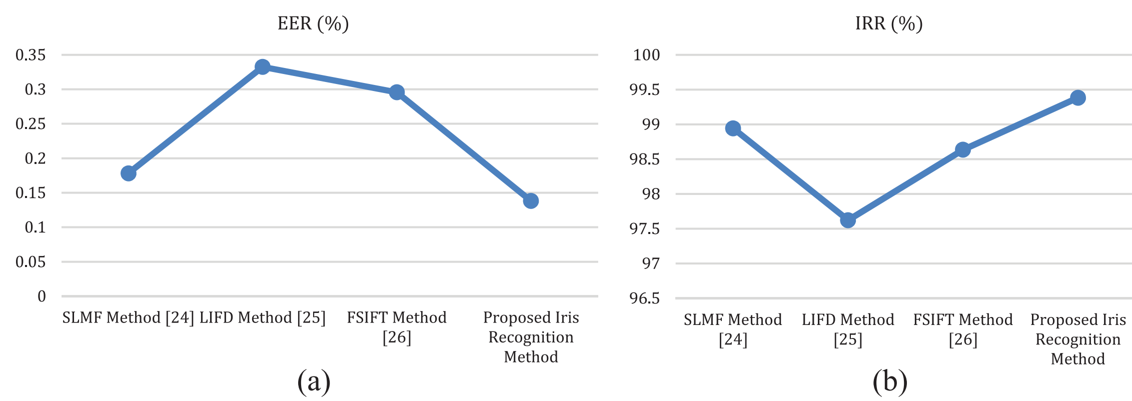


Figure 7: The recognition performance of different approaches on CASIA iris database

Table 2: The proposed method rates of iris recognition based on the number of training images and feature vectors dimension

Dimension of feature vectors/Images count per individual in training	1 (108 training images)	2 (216 training images)	3 (324 training images)	4 (432 training images)
80	89.5809	90.4506	91.3374	96.9135 (10/324)
120	92.6418	93.5412	94.4583	98.4567 (5/324)
160	94.9649	95.8868	96.8269	99.3827 (2/324)

When utilizing the proposed method with a total of 432 training images (4 images per individual) and 160 feature vectors, Table 3 demonstrates that the recognition performance reaches a peak level of 99.3827%.

Table 3: Iris recognition evaluation results

Numerical comparison methods	Total faces used in the test set	SURF method [10]	LGWHD method [11]	LIV method [12]	Proposed method
True positive	324	316	319	313	322
False positive	324	8	5	11	2
False negative	324	27	23	31	19
Iris recognition rate	324	95.5308	98.4567	96.6049	99.3827

However, we used the iris recognition rate in our evaluation [23]. We calculated the iris recognition rate as follows:

$$IRR\,(\%) = \frac{TNF - TNFR}{TNF} \times 100 \tag{17}$$

where:

$IRR\%$: Face Recognition Rate.

TNF: Total Number of Faces.

$TNFR$: Total number of False Recognition.

In addition, the Equal Error Rate (EER), Iris Recognition Rate (IRR) [23], True Positive (TP), False Positive (FP) and False Negative (FN) are expressed as numerical comparisons between different current techniques in the face recognition literature.

The numerical comparison of iris recognition using the Speeded Up Robust Features (SURF) method [10], the Log-Gabor wavelets and the Hamming distance method (LGWHD) [11], the Local intensity variation method (LIVM) [12], the supervised learning based on matching features (SLMF) [24], the local invariant feature descriptor (LIFD) [25], the Fourier-SIFT method (FSIFT) [26] on the CASIA database are shown in Tables 3 and 4, where 57% of samples for each individual are used in training set and 43% of the samples are used in the test set. The instinctive comparisons between these techniques in terms of EER and IRR are shown in Fig. 7.

Table 4: The iris recognition performance of different approaches on CASIA database

Methods	EER (%)	IRR (%)
SLMF method [24]	0.1782	98.9438
LIFD method [25]	0.4324	97.6227
FSIFT method [26]	0.2956	98.6356
Proposed iris recognition method	0.1381	99.3827

As shown in Fig. 7 and Table 4, we can see that the EER and IRR obtained by the proposed method are 0.1381% and 99.3827%, respectively. In fact, the proposed method clearly outperforms other approaches in terms of the use numerical comparison method. Also from Table 3, we find that the false positive rate (FPR) and false negative rate (FNR) are 5.8641% and 0.6172%, respectively, indicating that the proposed method achieves a higher accuracy rate.

4 Conclusion

In this work, we have presented a new method of human iris recognition based on a multilevel thresholding technique and a modified fuzzy c-means Algorithm. In the first phase, the edge detection technique is used to localize the iris in the original image. This step which decides the accuracy of matching, mainly localizes the outer boundaries of the iris. In the second phase, these regions' efficient segmentation is performed using the multilevel thresholding technique. Then, the statistical feature analysis method is used to ensure the acquisition of the iris characteristics essential for representation and identification. In contrast, the Fuzzy c-means algorithm is modified and employed for the classification task.

The evaluation and testing of the CASIA database prove the tool's validity and achieve its aim to recognize the human iris, which might require more attention. Furthermore, data fusion techniques will be included in future work to fuse and aggregate data from different information sources such as iris and fingerprint biometrics.

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