Eye Gaze Detection Based on Learning Automata by Using SURF Descriptor

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Abstract

In the last decade, eye gaze detection system has been known as one of the most important area activities in image processing and computer vision. The performance of eye gaze detection system is related to iris detection and recognition (IR). Iris recognition plays very important role for person identification. The aim of this paper is to achieve higher recognition rate compared to learning automata based methods. Usually, iris retrieval based systems consist of several parts including: pre-processing, iris detection, normalization, feature extraction and classification that are captured from eye region. In this paper, a new method without normalization step is proposed. Meanwhile, Speeded up Robust Features (SURF) descriptor is used to extract features of iris images. The descriptor of each iris image creates a vector with 64 dimensions. For classification step, learning automata classifier is applied. The proposed method is tested on three known iris databases; UBIRIS, MMU and UPOL database. The proposed method results in recognition rate of 100% for UBIRIS and UPOL databases and 99.86% for MMU iris database. Also, EER rate of the proposed method for UBIRIS, UPOL and MMU iris database are 0.00%, 0.00% and 0.008%, respectively. Experimental results show that the proposed learning automata classifier results in minimum classification error, and improves precision and computation time.

Keywords: Iris Retrieval; SURF; Learning Automata; Feature Extraction; Classification; Biometrics.

1. Introduction

A biometric system is based on unique features possessed by an individual. These features include: fingerprints, facial, voice, retina, iris and etc. Among these biometrics information, the system based on iris retrieval is more reliable and flexible for personal identification [1].

Eye gaze detection systems are based on iris retrieval. In generally, the iris retrieval system contains three steps. The first step is iris detection. The next step is locating the iris and the last step is a feature extraction from detected iris [2].

The performance of eye gaze detection systems depend on the extracted features from detected iris. There are many types of descriptor for feature extraction such as Histogram of Oriented Gradients (HOG), color, texture, Scale Invariant Feature Transform (SIFT), Principal Component Analysis (PCA) and etc. Boles et al applied zero-crossing representation of 1D wavelet transform for feature extraction [3]. The disadvantage of this method is to use 1D wavelet transform. This results in some drawbacks such as oscillations, shift variance, aliasing and lack of directionality [4]. In [5], Zhu et al presented 2D wavelet transform to extract features of iris images. However, 2D Wavelet transform is unable to resolve the aforementioned problems [6]. All natural signals are based on real-valued as speech, image and etc. Therefore, the reported method in [5] needed to use complex filtering. Montro et al reported a new method based on zero-crossing representation of 1D Discrete Cosine Transform [7]. They segmented iris image to its components by using Hough transform. The problem of this approach is to use 1D Discrete Cosine Transform (DCT). In the new methods, the 2D Discrete Cosine Transform along with zigzag scanning pattern are used which provide more information rather than 1D Discrete Cosine Transform [8]. Daugman applied 1D Gabor filter in feature extraction step [30]. In this method, the face is segmented as iris, gaze estimation and upper eyelid. The drawback of this method is as same as the reported method in [3]. In [9], the iris is separated by using circular Hough transform. In order to locate upper and lower eyelid, the authors applied Sobel edge detection operator. Belchar et al applied SIFT descriptor to extract features of iris [10]. The SIFT descriptor provides a feature vector with 128 dimensions. The high length of this vector corresponds to complexity.

The proposed system is evaluated on the three databases; UBIRIS [24] , UPOL [25] and MMU database

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[26]. In Figure 1, the examples of the iris images from these databases are shown.

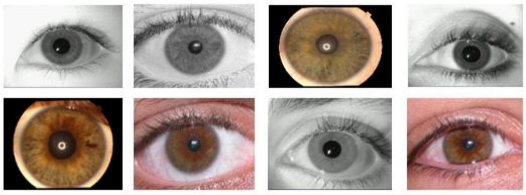

Fig. 1. Some example of UPOL, MMU and UBIRIS Database

This paper is organized as follows: in section 2, related works are discussed. Iris detection is explained in section 3. The proposed iris retrieval method is described in section 4. In this section, SURF descriptor, Learning Automata are explained. In section 5, experimental results are shown. Finally, the conclusion is drawn in section 6.

2. Related Works

Most of the reported method focuses on feature extraction and learns the features. In other words, after feature extraction, the next step is data learning. In this step, negative and positive images are used for training. Iris image is declared as positive and image without iris is considered as negative.

Liam et al [11] reported neural network for matching step. The authors used 150 samples for training. In this method, the authors extracted pupil by searching disk. The problem of this approach is to use disk, because size of pupil individual is different. Moinuddin et al [12] compared two different types of neural networks, MFNN and RBFNN. In [12], the edges are determined by using Sobel detector and then a feature vector is defined by iris boundary. The problem of this method is to use value of boundary as feature which is poor feature for training process in the algorithm. Ali and Salman [13] reported SVM classifier with different kernel types for iris retrieval. In this method, the features are extracted by Gabor wavelets. The disadvantage of this method is to use only the magnitude of Gabor filter output. Note that using both magnitude and phase of Gabor filter output provides higher recognition rate compared to using the magnitude alone [14]. In [15], Sarhan reported a method based on MLP neural networks. The method is followed by three-layer network. For feature extraction, this method exploits Discrete Cosine Transform (DCT). The problem of this method is as same as the reported approach in [5]. Fasca et al [16] exploited features by Local Binary Pattern (LBP) and HOG descriptors. The authors used Feed Forward Back Propagation Neural Network (FFBPNN) for training step. The authors applied two descriptors for feature extraction step which results in high computational complexity. Abiyer et al [17] applied neural network for iris retrieval system. The author described a gradient based learning model to learn their algorithm. In order to identify region of iris, they applied rectangular window with size of 10×10. The authors used same structure for iris detection. This results in high computational complexity by searching region of face. In [18], different types of learning algorithms for data classification are used such as Bayes, Euclidean, KNN probabilistic and non-probabilistic distance. Learning through kernel type corresponds to high computational complexity in learning step. In [19], iris retrieval method classified the iris images into multiple classes. The authors presented Principal Direction Divisive Partitioning (RDPP) to learn the iris images. For feature extraction, they proposed complex steerable pyramid. For iris detection, the authors suggested region of iris converted to 64 blocks. For each block, histogram is computed. Therefore, 24 histograms are defined as the features. The length of feature vector is too long and so results in high computational complexity. The reported method in [20] includes four stages. In first stage, the iris detection is applied on eye image to extract boundary between inner and outer contours. Then, iris image is segmented. In other words, the iris image is converted to new image with size of 16×16. The features are computed by using 2-D Gabor Wavelet Convolution. Finally, the reported approach is trained by Multi-dimensional artificial neural network (MDANN). The shortcoming of this method is as same as the reported method in [5]. In reported method in [21] is based on template matching. The segmentation is performed on captured iris image. Then for each iris image, the features are extracted by using Gabor filter. The authors generated iris template by encoding operation. Finally, the matching is performed between iris template and a new iris. The authors used Gabor filter which is unable to resolve same problem in [5]. Also, they used template matching for each iris image and therefore the test iris is compared to all irises image. This results in longer time in recognition step. The reported method in [22] performs the pre-processing operation on iris image. For feature extraction, texture feature is applied. In this step, the authors suggested using Local Binary Pattern (LBP) descriptor which provides five features for each iris as: Entropy, Variance, Inertia, the inverse of the contrast of the co-occurrence matrix (IDM) and Energy. They also used Gray Level Co-occurrence Matrix (GLCM) descriptor for iris image. Therefore, size of feature vector is 1×261. For iris retrieval, the algorithm is trained by probabilistic neural network. The problem of this method is to have long feature length. Therefore, this method needs much space to store the database of features. In reported method by Sachdeva and Kaur [44], iris is extracted from eye region by using iris template. Then, features are extracted from iris by Scale Invariant Feature Transform (SIFT). For learning step, SVM classifier is used. The precision of this method is 99.14% in IITD database. In [45], the authors used two classifiers, SVM and ANN classifier. For feature extraction, they applied 1D Log-Gabor wavelet technique. The precision obtained in UBIRIS database for ANN and SVM classifier are 92.5% and 95.9%, respectively.

The recent method is a conventional neural network (CNN). CNN is based on deep learning and consists of a number of hierarchical layers that provide unique features for each image. In these structures, CNNs are applied as iris segmentation [45]. Li and et al proposed a method that based on Convolutional Neural Networks (CNNs) [45]. For iris region, they used fully convolutional networks (FCN). The drawback of this method is applied fully image as input FCN networks. In other words, they ignored region of interest (ROI) for iris region. In [46], the different method compared to [45] was proposed for eye gaze detection. They used rough rule for ROI detection. In the next step and considering 21×21 mask, ROI was learned by using CNN.

Considering the mentioned problems, in this paper, a new method is proposed which provides a feature vector with length of 64 dimensions by SURF descriptor. Also, for training step, Learning Automata (LA) is used which is based on reinforcement learning. The main advantage LA compared to other methods is that the information is not required from the environment.

A block diagram of the proposed iris retrieval method is illustrated in Figure2. The first step is iris detection. In this part, the iris is identified from the eye or face image. The iris features are extracted by using SURF descriptor. The SURF descriptor is faster than SIFT descriptor and feature vector has 64 dimensions in length. LA classifier is used to train the proposed method. By using LA classifier, classification error in training phase tends to minimum. The obtained results from LA classifier shows that this method improves speeded up convergence, boundary separating between classes and reduces computation time [23].

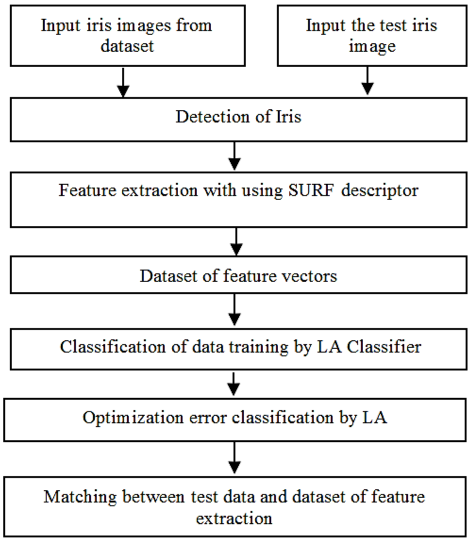

Fig. 2. Block Diagram of the Iris Retrieval Method

3. Iris Detection Method

For iris detection, the image is pre-processed to remove extra information (such as noise and etc.). Next step is segmentation. In this step, the image is divided into multi-sections. In this paper, k-means algorithm is used to segment the image. Normally, the normalization step is considered after segmentation step. However, in this paper, the normalization step is removed because we obtain same results with and without normalization. By removing this step, the computation time of the proposed method is improved. Next step is edge extraction of the iris image. We have designed for multi-scale and multi-directions [27]. Gabor wavelet is used to detect the edges. By changing the parameters of this wavelet, different scales are achieved. For creating each scale of iris image, Gabor filter is convolved with the original iris image in -90 to +90 degrees (Equations (1) [27]):

$$R(x-x_c, y-y_c)_{\lambda,\sigma,\theta,\varphi,\gamma} = R_0 \exp\left(-\frac{u^2+\gamma^2 v^2}{2\sigma^2}\right) \cos\left(2\pi\frac{u}{\lambda}\varphi\right) \quad (1)$$

$$u(x-x_c, y-y_c, \theta) = (x-x_c)\cos\theta - (yy_c)\sin\theta$$

$$v(x-x_c, y-y_c, \theta) = (x-x_c)\sin\theta + (yy_c)\cos\theta$$

In this equation, x_c and y_c are the rotation centers of the filter to the preferred angle, θ, that are placed related to the origin. σ, λ and φ are standard deviation, length wave and filter phase difference, respectively. After creating the edges by using different scales, these scales are combined together to present comprehensive edge map. Figure 3 shows the illustration of the iris detection method.

Fig. 3. The Results of Iris Detection Methods

4. Proposed Iris Retrieval Method

In this section, the iris retrieval method is explained. After iris detection, the features are extracted from the iris image. In this paper, SURF descriptor [28] is used which is later introduced in section 4.1. Then, the database of the feature vectors is created. According to this database, matching process is performed between the test image and all images. Next step is training. In this step, the LA classifier is used. By using Learning Automata, the classification error is optimized. In section 4.2, classification and optimization based on Learning Automata are introduced.

4.1 SURF Descriptor

The SURF algorithm reported in [28] is applied for four steps:

a. Scale-space extreme detection
b. Key point localization
c. Orientation assignment
d. Key point descriptor

In the first step, this descriptor uses the determinant Hessian matrix to find candidate points. The points considered as candidate points which have no changes against occlusion and orientation. The hessian matrix, $H(x,\sigma)$, at scale, σ, in x is defined as [28]:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \quad (2)$$

Where $L_{xx}(x,\sigma)$, $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$ denote the convolution of the image at point of $X(x,y)$. By changing the parameter, σ, different scales are achieved. In next step, each candidate point is compared to 8 points in the same scale, 9 points in the upper scale and 9 points in the lower scale. The point is considered as key point in which has extreme value between 26 neighbors of scales. After localization of the key points, orientation assignment is considered for each key point. The dominant orientation is estimated by calculating sum of the horizontal and vertical Haar wavelet responses within a sliding orientation window with angle of $\pi/3$.

Final step is constructed by a square window along with the dominant orientation with size of 20σ. This window is subsequently divided into 4×4 regular sub-regions. Then, for each sub-region, Haar wavelet responses are calculated. As shown in Figure 4, for the window containing 4×4 sub-region, each feature point can be described using a 64-dimensional vector. Figure 5 shows illustration of the iris image with extracted features by using SURF descriptor.

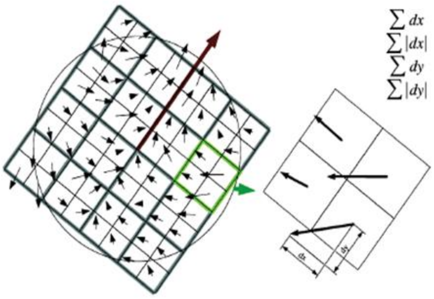

Fig. 4. Computed Features Vector

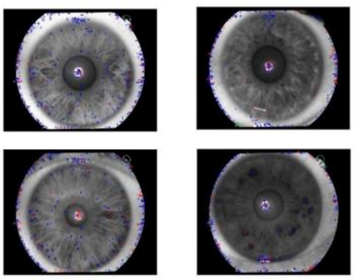

Fig. 5. Feature Extraction by SURF Descriptor

4.2 Learning Automata

4.2.1 Concept of Learning Automata

For the first time, learning automata (LA) was reported by Testlin in 1960s [29]. The LA can be considered as a single object which has a finite number of actions. Generally, the LA works by choosing an action from a set of actions and then this action is applied on the environment. This selection is evaluated by the random environment and for the next selection, the automata is used based on environment response. During this process, the automaton learns to choose its optimal action. During the last two decades, the LA has been widely used by researchers. For example in the pattern recognition area, it is suggested to use neural network for automation operation [30]. The authors reported NN[1] with arrange 9-3-1. In this arrange, 9 refers to the number of neurons input layer, 3 represents neurons middle layer and 1 indicates neuron of output layer.

In fact, learning automata is reinforcement learning. The main advantage of the LA compared to other methods is that no information is required from the environment. In supervision based methods, inputs and targets are already determined, but in reinforcement learning, automata must learn oneself. Reinforcement learning allows the method agent to learn its behavior based on feedback from the environment. This behavior can be learnt once for all, or kept on adapting by passing the time. If the problem is accurately modelled, some reinforcement learning algorithms can converge to the global optimum; this is the ideal behavior that maximizes the reward. This automated learning scheme implies that there is little need for a human expert who knows about the domain of application. Much less time will be spent for designing a solution, since there is no need for hand-crafting complex set of rules as expert system, and all that is required is someone who is familiar with Reinforcement learning.

In general, LA takes input β and changes its mode by using an internal function [31]. Then, output α is delivered to environment. Each learning automaton is characterized by a set of internal states, input actions or set of inputs, state probability distributions, and reinforcement scheme or set of outputs, which are connected in a feedback loop to the environment, as shown in Fig. 6 [30].

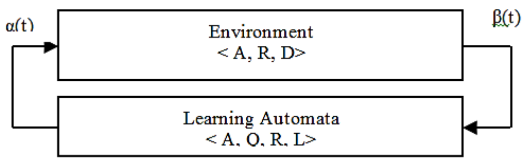

Fig. 6. Learning Automata in the Environment [30]

The learning is defined as a change in behavior resulted from past experience with the passage of time. At each step, an action is selected based on probability distribution. The environment responses to the selected action and accordingly sends a response to LA with either a reward or a penalty. By repeating these interactions, the automaton converges to the optimal action. In LA based methods, parameters are defined as follows:

- $A = \{\alpha_1, \alpha_2, \ldots, \alpha_r\}$ Presents set of actions with total number of r actions.
- R: This is limit for responses due to the environment.
- $D = \{d_1, d_2, \ldots, d_r\}$ Presents a set of reward or penalty probability.

[1] Neural Network

- Q: Presents state of automation by $(k) = \{p(k), \widehat{D}(k)\}$. Where $p(k)$ is the action probability and $\widehat{D}(k)$ is vector of reward or penalty probability.
- L: Presents the learning algorithm.

In this algorithm, $p(k)$ is changed in each iteration. If response of environment is penalty then:

$$p_j(k+1) = \begin{cases} p_j(k) + a(1 - p_j(k)) & \forall j = i \\ (1-a)p_j(k) & \forall j \neq i \end{cases} \quad (3)$$

Where a is reward parameter. If response of environment is reward, $p(k)$ is updated by Eq. 4:

$$p_j(k+1) = \begin{cases} (1-b)p_j(k) & \forall j = i \\ \left(\frac{b}{r-1}\right) + (1-b)p_j(k) & \forall j \neq i \end{cases} \quad (4)$$

Where b is penalty parameter.

Based on the relation between a, b, learning methods are defined as follows:

- If $a = b$, learning method is defined as Linear Reward Penalty (L_{R-P}).
- If $a \gg b$, learning method is defined as Linear Reward Epsilon Penalty ($L_{R-\varepsilon P}$).
- If $b = 0$, learning method is defined as Linear Reward Inaction (L_{R-I}).

4.2.2 Clustering Based On Learning Automata

In this section, clustering process is performed by using LA. After feature extraction, the feature vectors are stored in a database as features database. Then, a number of these vectors are considered as data training. Based on these vectors, training step is started. In this paper, we apply LA as shown in Figure 7. For each iris image and the length of SURF descriptor feature vector has 64 dimensions.

In this paper, LA classifier reported by S.H. Zahiri is used [23]. Based on feature vector, decision hyper plane is considered as follows:

$$d(x) = w_1x_1 + w_2x_2 + \cdots + w_{64}x_{64} + w_{65} \quad (5)$$

Where $X = (x_1, x_2, \ldots, x_{64}, 1)$ denotes the features which are extracted by SURF descriptor and $W = (w_1, w_2, \ldots, w_{64}, w_{65})$ is called weighted vector.

Normally, log_2^M is the number of decision hyper planes (M denotes the number of classes) which separates classes from each other. A data belongs to ith class if:

$$d_i(x) = w'_iX > 0 \qquad i = 1,2, \ldots, M \quad (6)$$

Where $d_i(x)$ denotes ith decision hyper plane and w_i is the weighted vector for ith decision hyper plane.

So far, the classes have been separated from each other. In this paper, the numbers of decision hyper planes based on separated classes are considered according to Eq. 7:

$$X\varepsilon C_i if \quad d_i(X) > d_j(X) \quad for\ all \quad j \neq i \quad (7)$$

Where C_i is ith class.

LA classifier provides the best vector weights for decision hyper planes. According to weight vector variable, $W_i (i = 1,2, \ldots, H)$, where H is the number of decision hyper plane, fitness function for data of iris is defined as:

$$f(W) = R(1 - \beta M) \quad (8)$$

Where R is the number of correct classified, β is a parameter which is experimentally obtained and M denotes the number of misclassified. In this paper, we consider $\beta = 0.5$.

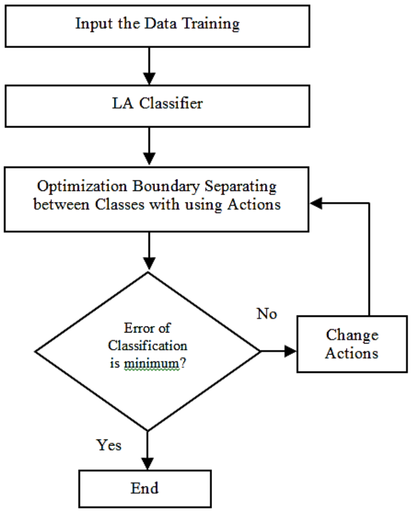

Fig. 7. Block Diagram Classification and Optimization by LA

The aim of the LA classifier is optimization of separating boundary between the classes or minimization of classification error, as shown in Fig. 7. In the following, the structure of the LA classifier is explained.

4.2.3 The Structure of LA Classifier

According to above descriptions, the LA classifier is based on minimization of Equation 6 which is performed in following steps [23]:

Step 1: Initialization of Internal Parameters

γ: Number of hyper planes
δ: Threshold of action probabilities
s: Normalized factor of convergence
ε: Error band

Step 2: Display of r Hyperplanes on Feature Space

According to each action, parameters are defined as:

- $\eta_i(n)$: Total rewards or penalties obtained by the action α_i.
- $z_i(n)$: Number of times in which the action α_i is chosen
- $\xi_i(n) = \frac{\eta_i(n)}{z_i(n)}$
- $\xi_m(n) = Max_i\{\xi_i(n)\}$
- $\xi_l(n) = Min_i\{\xi_i(n)\}$

$p(n)$: Action probability distribution of α_i

Step 3: Search Loop

- Repeat
- Pick up an action $\alpha(n) = \alpha_i(n)$ according to $p(n)$

- Randomly select a set of decision weight vector
- Calculate Equation 8
- Update $\xi_i(n)$ as follows:
- If $\alpha(n) = \alpha_i$, Then

$$\eta_i(n+1) = \eta_i(n) + \frac{T - f(W)}{T}$$

Where T is the total of training data.

- $z_i(n+1) = z_i(n) + 1$
- $\xi_i(n+1) = \frac{\eta_i(n+1)}{z_i(n+1)}$

For all $j \neq i$

- $\eta_j(n+1) = \eta_j(n)$
- $z_j(n+1) = z_j(n)$
- $\xi_j(n+1) = \xi_j(n)$

Update $p(n)$ as follows:

- $p(n+1) = \left(1 - s \times \xi_m(n)\right) \times p(n) + s \times \xi_m(n)$
- If $P_l(n) = Min_i\{p_i(n)\} < \delta$, Then Go to the next step
- Else, $n = n + 1$
- End Repeat.

This process continues until the classification error is minimized. Then, the best actions, weighted vectors, are stored as decision hyper planes. Figure 8 shows illustration of LA classifier and optimization on MMU, UBIRIS and UPOL database. As observed in Figure 8, for three databases, the convergence is occurred in few numbers of iterations. The error of classification is related to UBIRIS database, but the convergence of this database in compared to MMU and UPOL database has occurred later.

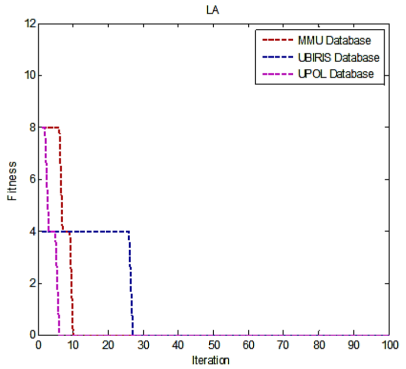

Fig. 8. The result of the LA classifier and optimization for three databases; MMU, UBIRIS and UPOL iris database

5. Results

The proposed method based on learning automata is implemented by MATLAB (version 8.1) with configuration as follows: processor: Intel core i5, OS: Windows 8, CPU speed: 2.50 GHz and RAM: 6 GB.

In this section, the performance of the proposed method is evaluated on three databases, UBIRIS, MMU and UPOL. The details of these databases are listed in Table 1. The MMU database is composed of 45 topics in which each topic contains 10 eye images, 5 eye images for left of eye and 5 images for right of eye [26]. The UBIRIS database is composed of 241 subjects [24]. The total numbers of image are 1877 images. The original size for each iris image is 800 × 600. The UPOL iris database is composed of 64 topics. Each topic includes six images, three left iris images and three right iris images [25]. Size of iris image is 768 × 576.

Table 1. The Number of iris images, size and the number of subjects

Database	Original size iris image	Number of iris image	Number of subject
MMU	320×280	450	45
UBIRIS	800×600	1877	241
UPOL	768×480	384	64

Meanwhile, for evaluation of the proposed iris retrieval method, we use two measures, Equal Error Rate (EER) and recognition rate. The EER is biometric measure that is composed of False Rejection Rate (FRR) and False Acceptance Rate (FAR) [32].

$$FRR = \frac{Number\ of\ misclass\ ified\ as\ iris\ samle}{Total\ Number\ of\ data\ in\ database} \tag{9}$$

$$FAR = \frac{Number\ of\ iris\ samle\ as\ misclass\ ified}{Total\ Number\ of\ data\ in\ database} \tag{10}$$

When FRR and FAR are equal, the obtained value is defined as EER. The reliable performance of iris retrieval occurs when EER is very low. In following, the experimental results for MMU, UBIRIS and UPOL databases are explained.

5.1 The MMU Database

We have compared the proposed iris retrieval to the reported algorithms in [33-34-35-36-22-48]. In [33], Elgamal et al reported a method based on DWT and PCA[1]. The authors used 2/3 images for training part and rest images for testing part. Using 1D DWT caused to extract poor feature compared to 2D DWT. The shortcomings of DWT are oscillations, shift variance, aliasing and lack of directionality [4]. In [34] and [16], Kumar et al used Haar wavelet and logarithm Gabor filter. They reported new sets for training with a number of variables. The disadvantage of this method is that the authors used only magnitude part of Gabor wavelet output. However, using magnitude and phase of Gabor filter output, provides higher recognition rate [44]. In [35], Rahulkar et al reported a new method based on triplet half-band filter bank. In this method, two samples are considered for training and three samples for testing. In [36], Baqar et al provided dual boundary contour vector. Using iris boundaries as features results in poor feature for training step. This method used three images for training and two images for testing. In [48], the author used different

[1] Principal Component Analysis

descriptor, Gabor, Riesz and Taylor. They also applied mixed descriptor to create new descriptor.

The recognition rate and EER measures resulted by the proposed method and the reported methods in [33-34-35-36-22] on the MMU database are presented in Table 2. As observed, the value of EER rate by the proposed method, Elgamal et al, Kumar et al, Rahulkar et al, Barqar et al and Hajari et al are 0.008%, 0.040%, 2.590%, 1.880%, 0.023% and 1.530%, respectively. Also, the recognition rate for the proposed method is 99.86%. Therefore, the proposed method provides the best performance in MMU database.

Table 2. Comparison of Recognition and EER rate in MMU database

Method	Recognition rate (%)	EER rate (%)
Elgamal et al [33]	99.50	0.040
Kumar et al [34]	81.37	2.590
Rahulkr et al [35]	87.18	1.880
Barqar et al [36]	99.00	0.023
Hajari et al [22]	95.50	1.53
Gabor [48]	85.50	--
Taylor [48]	97.50	--
Gabor+Taylor [48]	97.66	--
The proposed method	99.86	0.008

5.2 The UBIRIS Database

In this paper, we have used first session of this database due to having good quality images. In this sub-section, we compare the proposed method to the reported methods in [37-38-39-40]. The reported methods in [37], [38] and [39] used GLCM[1] based Haralic features, Gabor features with kernel Fisher and Gabor filter, respectively. The GLCM descriptor is based on texture analysis for iris image. The reported method in [40] is based on Gabor filter and uses only the magnitude. In [37] and [39], three samples are used in training step and two samples for testing part. In this database, we also use three samples for training and two samples for testing.

As observed in Table 3, the value of recognition rate by the proposed method, Sundaram et al, Tallapragada et al, Tsai et al, Naresh and reported method in [48] are 100%, 97.00%, 96.60%, 97.20%, 79.90%, 80%, 85%, 85%, 92.50% and 95.90%, respectively. As observed, the values of EER and recognition rate by the proposed method are 0.00% and 100%, respectively. The obtained results show that the performance of the proposed method is better than the other methods.

Table 3. Comparison of Recognition and EER rate in UBIRIS database

Method	Recognition rate (%)	EER rate (%)
Sundaram et al [37]	97.00	7.09
Tallapragada et al [38]	96.60	8.19
Tsai et al [39]	97.20	7.80
Narseh et al [40]	79.90	8.93
Gabor [48]	80.00	--
Taylor [48]	85.00	--
Gabor+Taylor [48]	85.00	--
ANN [45]	92.50	
SVM [45]	95.90	
The proposed method	100	0.00

[1] Gray Level Co-occurrence Matrix

5.3 The UPOL Database

In this database, we have compared the proposed method against the reported methods in [19-41-42-47]. In [19], Ross et al proposed complex steerable pyramid. The authors used the number variables of iris image for training. The authors in [41] and [42] proposed Coiflet wavelet transform and Haar, Symlet, biorthogonal, respectively. They presented three iris images for training and two iris images for testing part. In [47], the author used different descriptors to learn features. Also, theses descriptors are combined together to create new descriptor. In this database, we also use three samples for training and two samples for testing. As observed in Table 4, the recognition rate by the proposed method is 100%. As shown, the value of EER rate by the proposed method, Ross et al, Harjoko et al and Masood are 0.00%, 0.00%, 0.28% and 0.04%, respectively.

Table 4. Comparison of Recognition and EER rate in UPOL database

Method	Recognition rate (%)	EER rate (%)
Ross et al [19]	100	0.00
Harjoko et al [41]	82.90	0.28
Masoud et al [42]	95.90	0.04
HOG + KNN [47]	99.12	0.016
HOG + SVM [47]	87.14	0.18
LBP + KNN [47]	97.14	0.072
LBP + SVM [47]	90.69	0.12
The proposed method	100	0.00

The proposed method is also compared to the reported method in [43]. In [43], the authors reported a method in which multi-scale morphologic operator is used for feature extraction. In this experiment, iris retrieval is applied on two databases, UPOL and UBIRIS iris databases, for left and right iris images, and the obtained results are presented in Table 5. For example, the value of recognition rate left iris on UBIRIS database by the proposed method and Umer et al are 98.18%, 85.40%, respectively.

Table 5. Comparison of recognition rate left and right iris

Database	Method	Recognition rate (%)	
		L	R
UBIRIS	Umer et al [43]	85.40	91.56
	The proposed method	98.18	95.23
UPOL	Umer et al [43]	89.06	84.38
	The proposed method	97.51	85.19

One of the important measures in eye gaze detection is cost computational. We simulated by MATLAB (version 8.1) with configuration as follows: processor: Intel core i5, OS: Windows 8, CPU speed: 2.50 GHz and RAM: 6 GB. The cost computational on the MMU, UBIRIS and UPOL database are presented in Table 6.

Table 6. Comparison of the computational cost by the proposed method in terms of millisecond (ms).

The computational cost	
UPOL	52.10
MMU	56.11
UBIRIS	49.74

6. Conclusions

In this paper, a new method based on learning automata was proposed. The SURF descriptor was used for feature extraction. By using SURF descriptor, the proposed method improves performance, computation time and reduces the required storage space. Also, the LA classifier was applied for separating decision boundary. Meanwhile, by using LA, the classification error was minimized and tends to zero. The proposed method was compared to other methods on three databases including UBIRIS, UPOL and MMU iris databases. The obtained results show that the performance of the proposed method is better than other methods.

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