Iris segmentation using an edge detector based on fuzzy sets theory and cellular learning automata

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Iris-based biometric systems identify individuals based on the characteristics of their iris, since they are proven to remain unique for a long time. An iris recognition system includes four phases, the most important of which is preprocessing in which the iris segmentation is performed. The accuracy of an iris biometric system critically depends on the segmentation system. In this paper, an iris segmentation system using edge detection techniques and Hough transforms is presented. The newly proposed edge detection system enhances the performance of the segmentation in a way that it performs much more efficiently than the other conventional iris segmentation methods.
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1. Introduction

Reliable authentication of human identity has become necessary since the demand for security has grown in recent years. Traditional authentication methods, such as usernames, passwords, and identification cards, can easily be forgotten, lost, cracked, or even forged. Thus, a tremendous interest in biometric authentication technologies, which exploit automated methods of distinguishing individuals based on their physiological or behavioral characteristics, has risen in today's organized society. Physiological biometrics systems authenticate individuals based on the direct measurements of a body part, such as fingerprints, face, retina, and iris, while behavioral biometric systems measure the characteristics of an action, such as gait or signature [1,2].

The iris is the "colored ring around the pupil through which light enters the interior of the eye." [3]. The size of the iris is controlled using two muscles to adjust the amount of light entering the pupil. The pupil is typically darker than the iris, but may contain specular highlights. The sclera, a white region of connective tissue and blood vessels, surrounds the iris. Figure 1 depicts a sample image acquired by a commercial iris recognition system and marks the important features of an eye. The iris has a rich pattern of furrows, ridges, and pigment spots, which are believed to be determined randomly during the fetal development of the eye.

Because of its many advantages, iris recognition technology is one of the most stable and reliable biometric authentication methods. Most iris patterns do not change at all over a life time and are extremely difficult to modify or forge [4,5]. Moreover, each person has a unique iris pattern with high degrees of freedom [6]. However, authentication may be done incorrectly on images which can be categorized as nonideal due to off-angles, noise, blurring and occlusion by eyelashes, eyelids, glasses, and hair, even using the most efficient methods.

Obtaining desirable images makes the first phase of any iris recognition system, acquisition, very

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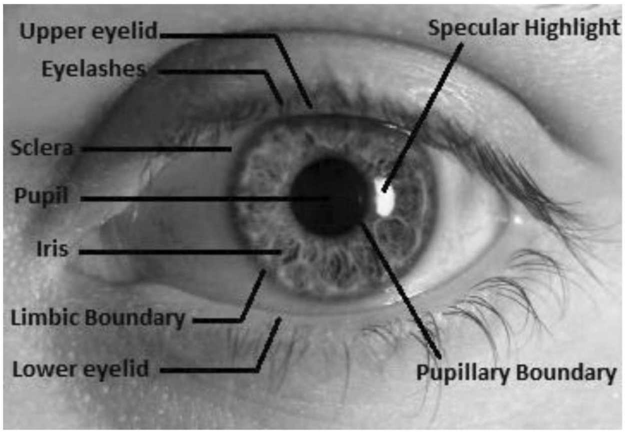

Fig. 1. Features of an eye.

important. In this paper, we have used standard iris datasets, which will be named later; therefore, we will not be focusing on the aforementioned phase anymore. Preprocessing, the second phase of a typical iris recognition system, which provides an accurate and desirable iris region in the image for the subsequent phases, consist of three steps: segmentation, normalization, and enhancement. The paper presents an iris segmentation method; thus, we will mostly concentrate on this step. The third phase, which is feature extraction, reduces the size of an iris model and its combination with feature selection improves classifier accuracy, and eventually, the last phase, matching, is performed by comparing the features of the template iris with a set of features of the candidate iris to determine the identity match [7].

Accurately separating the actual iris area from the eye image is a critical step in iris recognition, because the efficiency of all the steps and phases following the segmentation depends greatly on locating the iris. This is why, in this paper, a conventional iris segmentation method, based on an edge detector and Hough transform, is improved using an efficient edge detection approach. This method assumes that the inner and outer boundaries of an iris are circular, which in a small percentage of the eyes are not. However, this study can provide the opportunity for future researchers to develop new and more accurate iris segmentation methods based on the robust edge detector used in this study.

The rest of the paper is organized as follows. Section 2 reviews the background and history of iris segmentation. Section 3 describes the proposed edge detection method in details. Section 4 is dedicated to explaining the iris boundary segmentation approach. The experimental results are analyzed in Section 5, and finally, the paper is concluded in Section 6.

2. Background and Related Work

Iris as an biometric was first suggested over 100 years ago [8]. However, it was not until 1987 that Flom and Safir [9] brought a conceptual design of an automated iris biometric system to the table. In their design, in order to extract iris descriptors, they suggested the use of pattern recognition tools including difference approach, edge detection algorithm, and the Hough transform. To separate the pupil from the iris, they proposed an algorithm that finds large connected regions of pixels with intensity values below a given threshold. Flom and Safirs's recognition system, though being only conceptual, included many details such as the conditions for the image acquisition phase. Their system included a headrest, a target image to direct the subject's gaze, a variable illumination to force the pupil into a predetermined size, and a manual operator. These imaging conditions are typically impractical, but their basic algorithm has influenced the later research greatly.

Johnson [10], in a later report, confirmed the advantages of the use of iris as a biometric. He concluded, based on imaging experiments, that the pattern of an individual iris remained unchanged for 15 months.

In 1994, Daugman proposed a practical iris recognition system in a patent [11]. The concepts in Daugman's work have become a standard reference model for all future iris recognition systems. Daugman's method uses a video camera to acquire a digitized image of the to-be-identified human eye. In order to locate the part of the image that corresponds to the iris, Daugman approximates the pupillary and limbic boundaries of the eye as circles. The method proposed by Daugman tries to find circles in the image with maximum gray-level differences with its neighbors. Because of the considerable contrast between the iris and the pupil, the inner boundary can be described with three parameters: the radius r, and the coordinates of the center of the circle, x_0 and y_0. The parameter space can be searched using an integro-differential operator

$$\max(r, x_0, y_0)\left| G_\sigma(r) \times \frac{\partial}{\partial_r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} \mathrm{d}s \right|, \qquad (1)$$

where $G_\sigma(r)$ is a smoothing function, and $I(x,y)$ is the image of the eye. $G_\sigma(r)$ can be a function such as a Gaussian of scale σ. The complete operator behaves in effect as a circular edge detector, blurred at a scale set by σ, that searches iteratively for a maximum contour integral derivative with an increasing radius at successively finer scales of analysis through the three parameter space of center coordinates and radius (x_0, y_0, r) defining the path of contour integration [12].

After locating the inner boundary, the outer boundary can be detected using the same operator with different parameters. Daugman even thought of the occlusion of the eyelids and eyelashes. He changed the curve of the integral to find an arc which could accurately detect iris boundaries.

Many of the early research done on iris segmentation assume that the iris has a circular boundary. However, the pupillary and limbic boundaries may be not perfectly circular. Daugman, himself, has studied alternative segmentation techniques to avoid such a shortcoming [12].

After the extraction of the iris, Daugman suggested mapping the extracted region into a normalized coordinate system in order to facilitate the comparison of the iris features. Since this paper is mainly focused on the segmentation step, normalization will not be discussed any further. As mentioned earlier, Daugman has done some recent studies to improve his own work [12]. He proposed using active contour models for iris localization, handling off-axes gaze samples using Fourier-based methods, using statistical methods for eyelash detection, and normalization in large number database.

In 1997, Wildes [13] described a new iris biometric system. Apart from the image acquiring phase of the two approaches differing completely, Daugman's method looks for a maximum in an integro-differential operator that responds to circular boundaries to localize the iris, while Wildes' method creates a binary edge map of the image and detects circles using a Hough transform.

Comparisons between the Wildes' and Daugman's segmentation methods illustrate that although Wildes' approach is expected to be more stable to noise perturbation, it makes less use of the available data due to binary edge abstraction, and therefore might be less sensitive to certain details. However, this lack of sensitivity might even help the accuracy in terms of avoiding the undesired features. Wildes' approach also encompassed eyelid detection and localization.

Variations of the edge detection and Hough transform approach have been used by a number of researchers [14–16] since Wildes' method. The segmentation method proposed in this paper is based on Wildes' approach too. The edge map of the image is created using a robust edge detection method, and then using Hough transform, the boundaries of the iris are extracted. As mentioned earlier, not all of the irises are circular and modifications must be made to detect elliptical or even irregular irises accurately. However, the focus of this paper is on presenting the significantly improved results using the edge detection method that can open the door for future researchers to more robust iris recognition systems. The proposed method will be explained in details in the next Section.

3. Fuzzy and Cellular Learning Automata Edge Detection

Previously-common edge detection techniques, such as the Roberts edge operator, Prewitt edge operator, and Sobel edge operator, used first-order derivative operators. If a pixel falls on the boundary of an object in an image, its neighborhood will be a zone of gray-level transition. The Laplacian operator is a second-order derivative operator for the functions of two-dimensional operators and is used to detect edges at the locations of the zero crossing. However, it will produce an abrupt zero crossing at an edge, and these zero crossings may not always correspond to the edges. The Canny edge detector [17] is another gradient-based method which is used to determine a class of optimal filters for different types of edges, for instance, step edges or ridge edges. A major point in Canny's work is that a trade-off between detection and localization emerges. As the scale parameter increases, the detection increases and localization decreases. The noise energy must be known in order to set the appropriate value for the scale parameter. However, it is not an easy task to locally measure the noise energy because both noise and signal affect any local measurement.

On the other hand, Ulam and Von Neumann, first proposed cellular automata (CA) with the intention of achieving models of biological self-reproduction [18,19]. Later, Amoroso and Cooper described a simple replicator established on parity or modulo-two rules [20]. Then, it was followed by Stephen Wolfram, who has formed the CA theory. Nowadays, CA are widely used in many tasks due to their useful characteristics and various functions. Cellular learning automata (CLA) are models for systems that consist of simple components, and behavior of each component is obtained and reformed upon the behavior of its neighbors and their previous behavior. The constructing components of these models can execute robust and complicated tasks by interacting with each other. Hence, CLA are widely used in many areas of image processing such as denoising, enhancing, smoothing, restoring, and extracting features of images.

Fuzzy sets theory [21], originally proposed by Zadeh, has also been successfully applied to many image processing and pattern recognition problems, one of which is to detect edges or even enhance the already-detected edges. As a result, a better edge map can be obtained by fuzzy rules than by classical methods.

In this Section, we describe our proposed edge detector. Initially, the original image, which in this case is an eye, is divided into $w \times w$ sized windows, for each of which the membership function is then found using fuzzy sets. Subsequently, all the edges of the image, including the thick and unwanted ones, are detected. If the predefined patterns match each $w \times w$ window, the central pixel is penalized, otherwise rewarded. Later, the final image is produced using thresholding. There are two main steps involved in the edge detector as given below.

A. Extracting Edges Using Fuzzy Sets Theory

In recent years, many fuzzy techniques for edge detection have been suggested [22,23]. The edge pixels are the pixels whose gray levels have high differences with the gray levels of their neighborhood pixels. However, the definition of "high" is quite fuzzy and application-dependant. Hence, to deal with this ambiguity and vagueness, an edge image should be defined according to the fuzzy concept. In this Section, a fuzzy approach, which can detect edges accurately within a reasonable time [24], is used for preprocessing. The purpose of using such a technique is to determine a proper membership function for image pixels.

1. *Images as Fuzzy Sets*

Let an $M \times N$ matrix be the set of all pixels of image X and $g_{mn} \in [0, L]$ be the gray level of each pixel at the position (m, n). X can also be considered as an array of fuzzy singletons $\mu_{mn} \in [0, 1]$ that indicate the degree of brightness of each pixel [24]:

$$X = \bigcup_{m=1}^{M} \bigcup_{n=1}^{N} \frac{\mu_{mn}}{g_{mn}}. \tag{2}$$

2. *Membership Function*

In order to obtain a highly robust edge detector, we have tried to design very precise and therefore efficient membership functions. In most edge detectors, the criteria for edginess in a typical edgy area is the relatively high difference between the maximum and minimum gray levels. It should be noted that the fact mentioned above depends on the strength of the edges. One important point which is usually overlooked, however, is that in noisy environments the difference between the maximum and minimum gray levels can also be high. To avoid facing the problems regarding noisy environments, another condition is stated. The gray-level intensity of the center pixel in an optimal edgy neighborhood must be between the minimum and maximum gray levels. In other words, if the difference between $g_{\min}$ and $g_{\max}$ is high and the center pixel equals the mean or median of the neighboring pixels, then the edginess is considered to be high. If the center pixel $g_{\min}$ is surrounded by a $w \times w$ neighborhood, the proposed membership functions are as follows:

$$\widehat{\mu}_{mn}^{1} = \min\left(1, \frac{\max\limits_{i,j\in[1,w]} W(i,j) - \min\limits_{i,j\in[1,w]} W(i,j)}{\Delta_1}\right), \tag{3}$$

$$\widehat{\mu}_{mn}^{2} = 1 - \min\left(1, \frac{g_{mn} - \operatorname*{MeanMed}\limits_{i,j\in[1,w]} W(i,j)}{\Delta_2}\right), \tag{4}$$

where g_{mn} is the gray level of each pixel, $\Delta_1 > \frac{L}{4}$ and $\Delta_2 < \frac{L}{4}$ are meaningful boundaries, which have been obtained through experiments, for the parameters. The value of Δ is set to be 64 in order to reach the best possible result. W represents the mask which can be of any $w \times w$ size. In this paper, the mask is a 3×3 window. MeanMed is either the mean or med value.

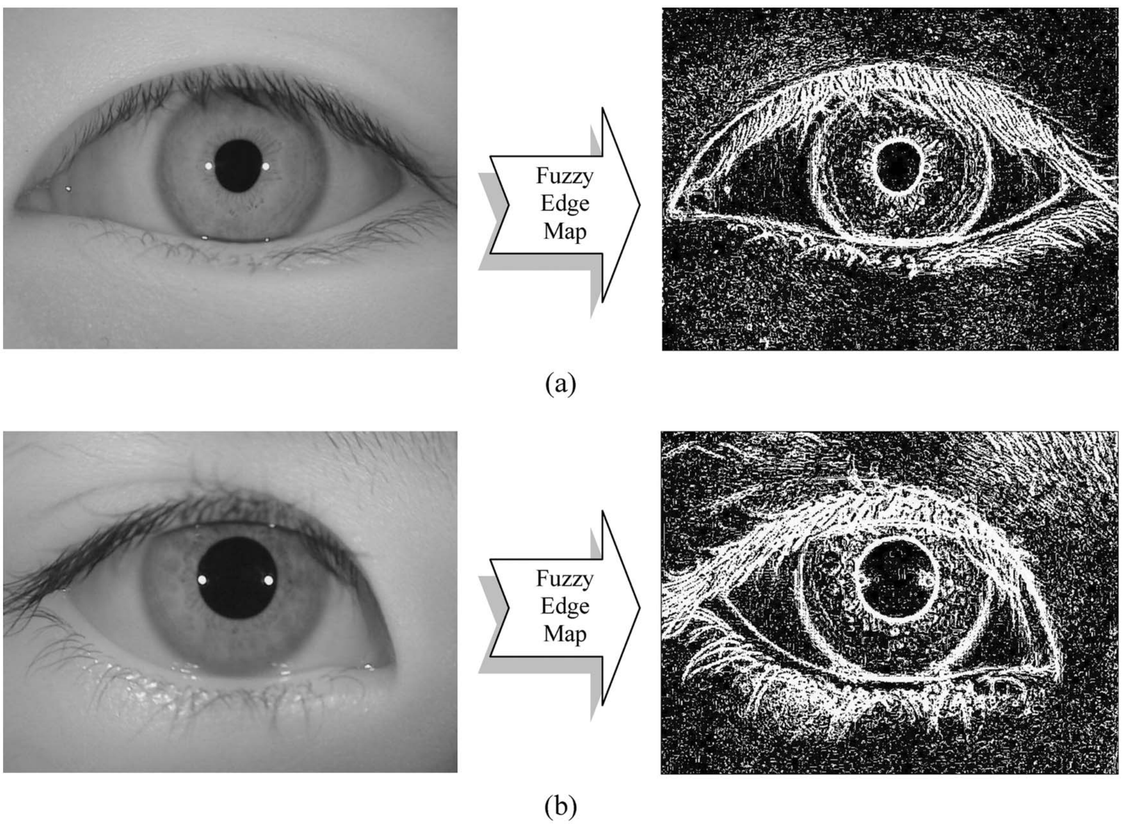

Fig. 2. Performance of the fuzzy preprocessing stage of the edge detector.

The image X', which is the normalized image, containing all the edges is

$$X' = \bigcup_{m=1}^{M} \bigcup_{n=1}^{N} \frac{\min(\widehat{\mu}_{mn}^{1}, \widehat{\mu}_{mn}^{2})}{g_{mn}}. \tag{5}$$

Figure 2 illustrates two examples of how the preprocessing stage of the proposed edge detector works on eye images. The original image and the edge map are both presented for comparison. The images were extracted from public databases which will be named later.

B. Enhancing the Edges by CLA

Learning automata (LA) are systems which can have infinite states. Each selected state is evaluated in a probabilistic environment and by means of a positive or negative signal, the result of the evaluation, which an automaton uses to determine the next state, is given to the automaton. Interaction between the probabilistic environment and LA is better shown in Fig. 3.

The ultimate goal, here, is to teach an automaton how to select the best state from all the possible choices. The best state is a state that maximizes the reward received by the environment. Environment can be described by the triplet $E = \{\alpha, \beta, c\}$, where $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_r\}$ is a set of inputs for LA, $\beta = \{\beta_1, \beta_2, \ldots, \beta_m\}$ is a set of outputs, and $c = \{c_1, c_2, \ldots, c_r\}$ is a set of penalty probabilities. A variable structure learning automaton is described by the quadruplet $\{\alpha, \beta, \rho, T\}$, where $\alpha = \{\alpha_1, \alpha_2, \ldots, \alpha_r\}$ is a set of states, $\beta = \{\beta_1, \beta_2, \ldots, \beta_m\}$ is a set of inputs, $\rho = \{\rho_1, \rho_2, \ldots, \rho_r\}$ is the probability vector of choosing each state by LA, and $\rho(n+1) = T[\alpha(n), \beta(n), \rho(n)]$ is the learning algorithm.

In many cases, LA cannot perform the learning task properly. Because of this fact, a new system called the cellular learning automaton is developed from combining the CA and LA [25]. We can use different kinds of neighborhoods in the CLA. In general, each set of cells can be considered as a neighborhood, but the most common kinds of neighborhoods are Von Neumann, Moore, Smith, and Cole, which are known as "nearest neighbors" neighborhoods. These neighborhoods are illustrated in Fig. 4.

The CLA environment can be described by the triplet $E = \{\alpha, \beta\}$, where α is the probability increase coefficient for CLA and β is the probability reduction

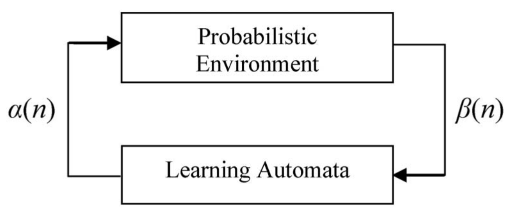

Fig. 3. Interaction between the probabilistic environment and LA.

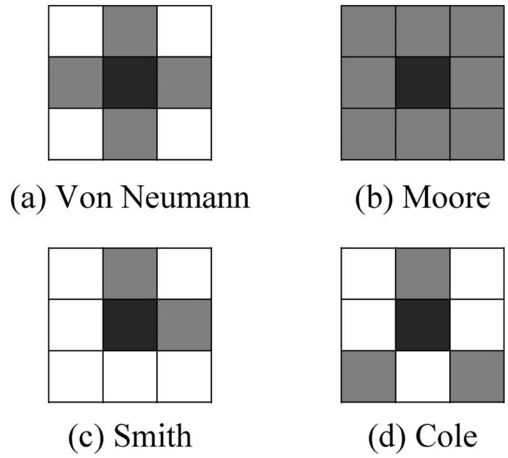

Fig. 4. Different types of neighborhood.

coefficient. A variable structure cellular learning automaton is described by the quadruplet $\{\alpha, \beta, \rho, T\}$, where ρ is the value of every pixel (brightness) and $\rho(n+1) = T[\alpha, \beta, \rho(n)]$ is the learning algorithm.

By using the CLA together with a set of rules, the detected edges of the previous phase are enhanced. In this phase, each cell of the image is considered to be a variable structure learning automaton, which has relations with its neighboring automata by a Moore neighborhood of radius 1. Each learning automaton has two states: edge and nonedge. The initial state of each learning automaton is determined by the final image X' of the the preprocessing phase. Local rules of these CLA are defined in a way that in continuous repetitions strengthen edge pixels and weaken nonedge pixels and noises. It should also be able to strengthen edge pixels that are in the middle of two edge pixels, which are detected as a nonedge pixel or a weak edge, and on the other hand, be able to weaken nonedge pixels which are detected as strong edges. The center of each template is placed at each pixel position (i, j) over the normalized image. Each time, all the LA in a cellular learning automaton select a state from their set of states. This selection can be based upon either prior observations or random selection. Each selected state, with respect to neighboring cells and the general rules, receives a reward or a penalty.

In order to improve the edges, certain patterns have been defined that represent the noises and the detected edges that are either thick or unwanted. The choice of patterns, which reflect the type and direction of the edges, is crucial for the accuracy of the method. Figure 5 illustrates these patterns that result in a penalty. In these patterns, the white cells are the edges and the black cells are the nonedges. Other patterns that receive penalty can be obtained by rotating or flipping the patterns in Fig. 5. Because of the similarities, these patterns are not shown in Fig. 5. All the other patterns receive a reward. The process of updating cells and giving penalties and

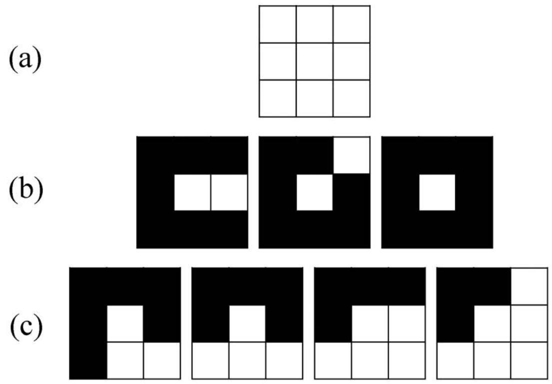

Fig. 5. Penalty patterns. (a) Thick edge. (b) Noises. (c) Unwanted edges.

rewards continues until the system reaches a stable state or satisfies a predefined condition (such as a certain number of iterations).

Figure 6 depicts two examples of how the CLA enhances the edge map generated by the fuzzy preprocessing stage of the edge detector. The final image of the preprocessing phase, and the one obtained by the CLA are shown in Figs. 6(a) and 6(b), respectively. It is clearly noticeable that the CLA image contains a smaller amount of noise and much more precise edges.

Penalties and rewards given to each cell of the CLA are calculated by Eqs. (6) and (7), respectively,

$$\begin{aligned} \rho(n+1) &= (1-\beta)\rho(n) \\ \rho(n+1) &= \beta(255-\rho(n)), \end{aligned} \tag{6}$$

$$\begin{aligned} \rho(n+1) &= \rho(n) + \alpha(255-\rho(n)) \\ \rho(n+1) &= (1+\alpha)\rho(n), \end{aligned} \tag{7}$$

where α is the probability increase coefficient and β is the probability reduction coefficient ($\alpha > \beta$). The learning process of each learning automaton is implemented with values of $\alpha = 0.01$ and $\beta = 0.001$. In Eqs. (6) and (7), the upper formulas change the brightness of the pixel in the center of the mask, and lower formulas change the brightness of the neighboring pixels in the mask. The framework of the proposed edge detector is illustrated in Fig. 7, and its performance is better described in the following algorithm.

Proposed Edge Detection Algorithm

Step 1. Read the original image.

Step 2. Divide the original image into overlapping 3×3 windows.

Step 3. Calculate membership functions $\widehat{\mu}^1_{mn}$ and $\widehat{\mu}^2_{mn}$ for each cell of image to form an edgy image.

Step 4. Form 34 edge-detected templates as shown in Fig. 5.

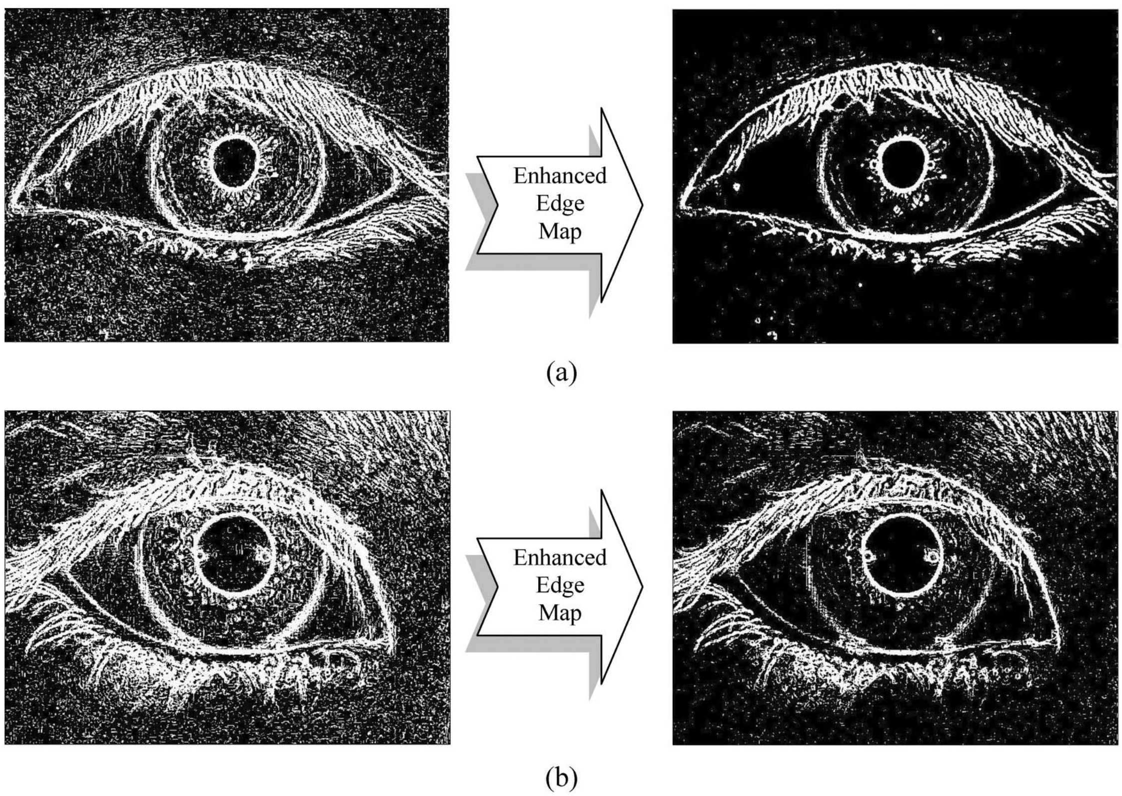

Fig. 6. Comparison between the products of (a) the fuzzy preprocessing stage and (b) the CLA enhancement stage .

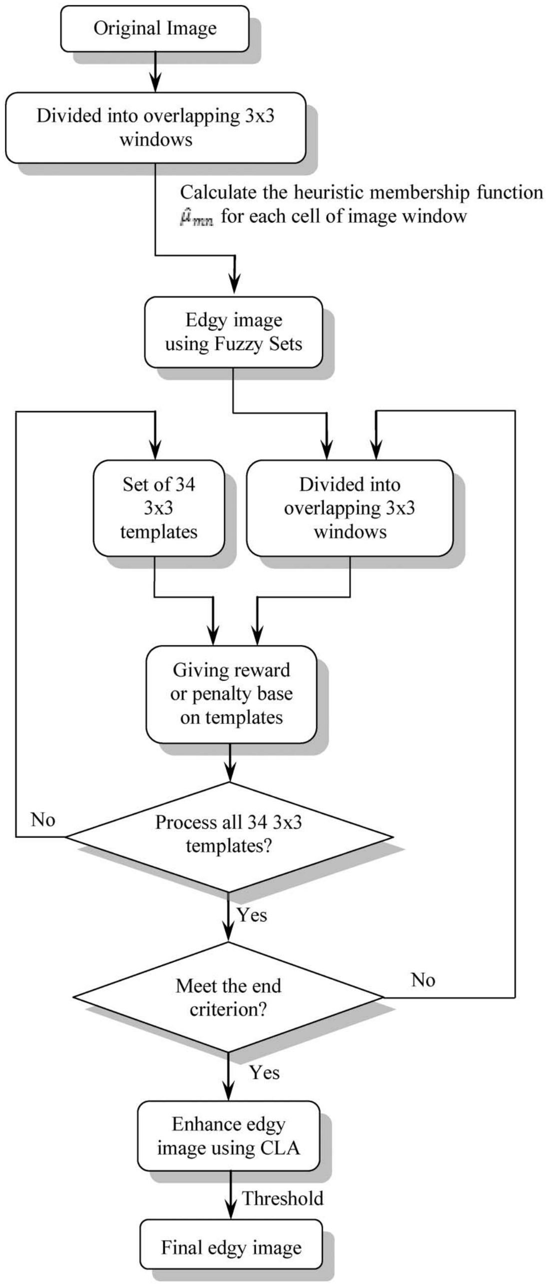

Fig. 7. Framework of the proposed edge detector.

Step 5. Apply the edge templates over the image by placing the center of each template at each point (i, j) in the edgy image.

Step 6. Apply the penalties and rewards defined in Eqs. (6) and (7) to each pixel.

Step 7. Threshold the obtained image.

Step 8. An edge-detected image is obtained.

4. Iris Boundary Segmentation

As mentioned before, iris segmentation phase plays a critical role in the performance of the iris recognition system. In the proposed method, circular Hough transform is used for detecting the iris and pupil boundaries. The first stage to guarantee an accurate segmentation is generating a desirable edge map. After applying the Fuzzy-CLA edge detection method on the image, gradients that were biased in the vertical direction for the outer iris/sclera boundary as suggested by Wilds [13] were used. Vertical and horizontal gradients were weighted equally for the inner iris/sclera boundary. The Hough transform for the outer iris/sclera boundary was performed first and the Hough transform for the inner iris/pupil boundary was performed within the iris region to make the circle detection process more efficient and accurate.

The proposed method, like many conventional methods, is based on the assumption that both the inner and outer iris boundaries are circular. Although, in actuality, the iris boundaries can be elliptical or irregular, the proposed method solely focuses on the advantages that the new edge detection method can bring upon the system. The process of segmentation is illustrated in Fig. 8.

As mentioned earlier, the proposed method focuses on the segmentation phase so the normalization phase is briefly described in the following.

Before using the proposed method for iris recognition, it is required to normalize the iris image, so that the representation is common to all, with similar dimensions. The normalization process involves unwrapping the iris and converting it into its equivalent polar coordinates. The circular iris area is transformed into a block. This normalization process alleviates the effects of pupil size variation upon the iris recognition results and, thus, it is adopted in most of the iris recognition methods. However, if the recognition results are not satisfactory, then a nonlinear deformation model should be considered.

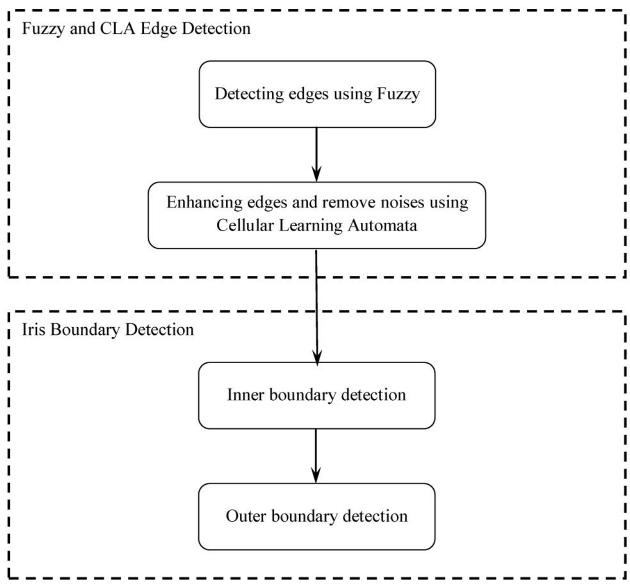

Fig. 8. General framework of the proposed iris segmentation approach.

5. Experimental Results

In this Section, the results obtained from a series of experiments conducted on standard eye images are analyzed and discussed. The performance of the edge detection method has been explained before and now the accuracy of the iris segmentation method based on the proposed edge detector is compared with that based on the Canny and Sobel edge detectors, which are commonly used.

Two public databases were used in our experimentation process. CASIA-IrisV3 [26] contains 22, 051 iris images which are all gray-level images captured with near-IR illumination.

The UBIRIS.V1 database [27] is composed of 1877 images incorporated with several noise factors, simulating less constrained image acquisition environments. The images were captured in two sessions, in the first of which noise factors relative to reflections, luminosity, and contrast were minimized. The images collected at the second session simulated the ones captured by a vision system with or without minimal active participation from the subjects, adding several noise problems. Overall, the images obtained from the CASIA-IrisV3 can be considered as having desirable quality while the images of the UBIRIS.V1 are of relatively poor quality.

Most iris segmentation methods can detect the pupil correctly, but many, including the proposed method, cannot segment certain pupil areas accurately since the pupils are sometime noncircular or even nonelliptical. In order to evaluate the accuracy of the segmentation method, 400 images were selected from the CASIA-IrisV3 database and 100 images from the UBIRIS.V1. Several experiments were done on the images using the proposed method based on the Fuzzy and CLA edge detector, the segmentation method based on the Canny edge detector, and the segmentation method based on the Sobel edge detector. Since the Hough transform is used in all these

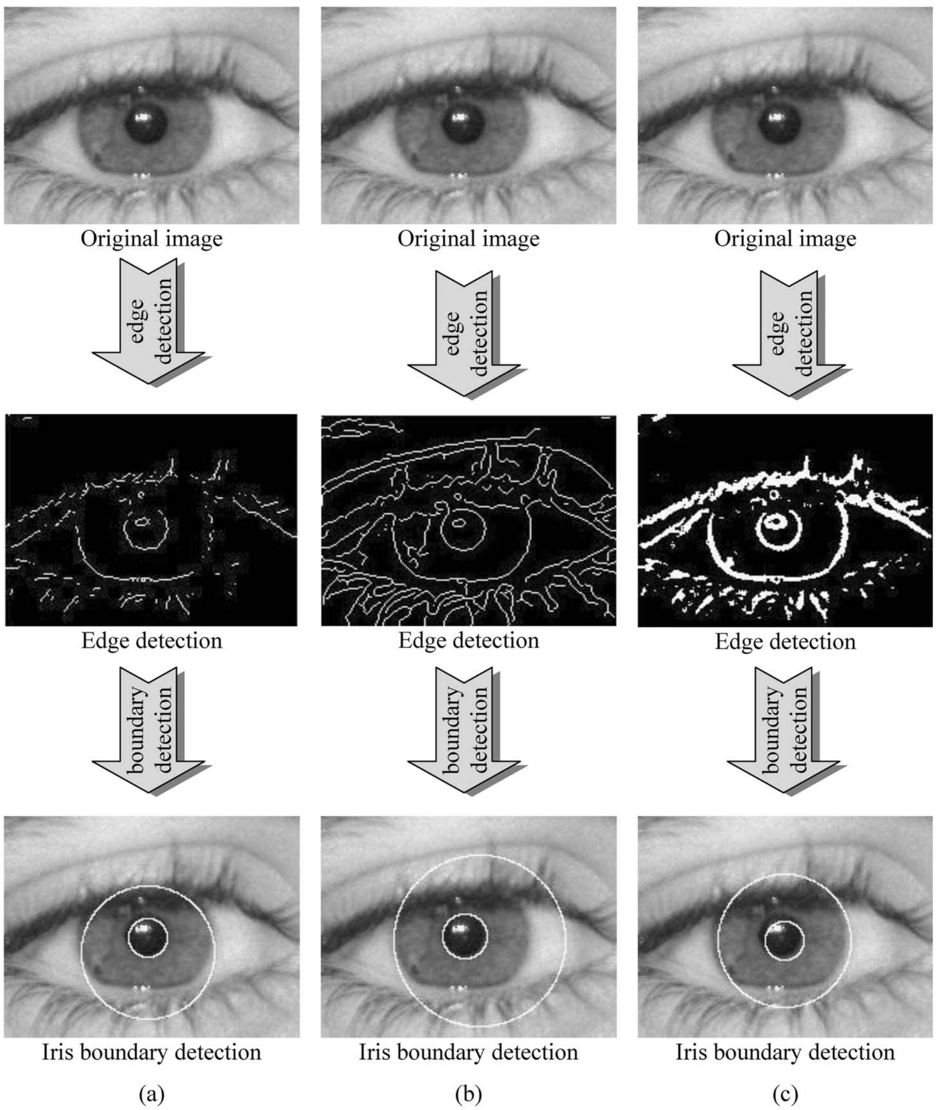

Fig. 9. Noncircular irides that could not be detected accurately using the segmentation method based on (a) the Sobel edge detector, (b) the Canny edge detector, and (c) the proposed edge detector.

methods, some noncircular irides are not segmented accurately, as seen in Fig. 9.

This paper is aimed to propose an improved conventional method using an efficient edge detector. Canny and Sobel are both robust and accurate edge detection methods which have been used frequently in the past. As it is seen in Fig. 10, in most cases with circular pupils, the pupil and the iris are both segmented accurately using the proposed method and the segmentation approach based on the Canny edge detector, but the Sobel-based segmentation method fails in detecting the iris correctly.

Since the proposed edge detector has the ability of weakening the noise pixels and detecting the accurate edge map of the image, which is an advantage the Canny edge detector lacks, for noisy images,

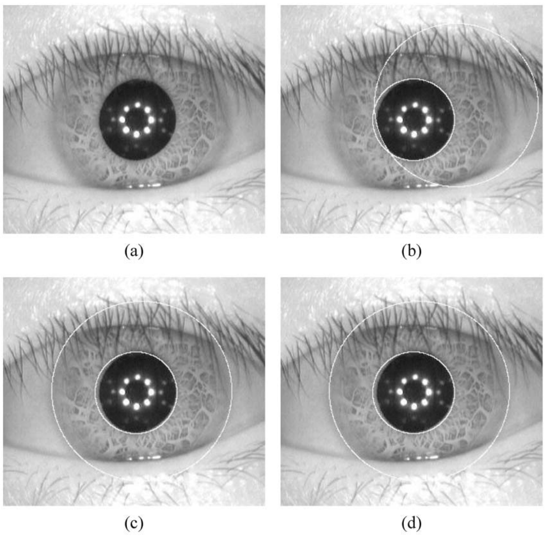

Fig. 10. (a) Original image, (b) image obtained from the Sobel-based segmentation method, (c) image obtained from the Canny-based segmentation method, and (d) image obtained from the proposed segmentation method.

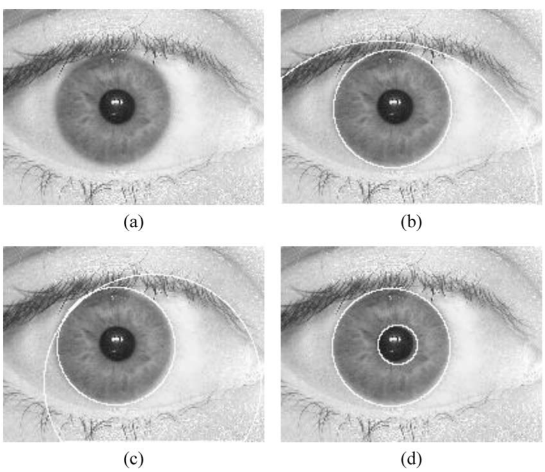

Fig. 11. (a) Original image, (b) image obtained from the Sobel-based segmentation method, (c) image obtained from the Canny-based segmentation method, and (d) image obtained from the proposed segmentation method.

Table 1. Iris Detection Accuracy Rate for the Aforementioned Methods

	Iris Detection Accuracy Rate (%)	
Segmentation Method	CASIA-IrisV3 (400 Images)	UBIRIS.V1 (100 Images)
Sobel-based method	78	53
Canny-based method	91.75	69
Proposed method	96.75	86

mainly found in the UBIRIS.V1 database, the proposed method can segment certain irides accurately that the segmentation method based on the Canny edge detector cannot. As seen in Fig. 11(c), the Canny edge detector has generated such an inaccurate and noisy edge map that the entire eye is taken as the limbic boundary (outer boundary), and the iris is considered the pupillary boundary (inner boundary). Figure 11(b) illustrates that the Sobel method behaves in the similar manner, but the proposed method can detect both the limbic and papillary boundaries accurately as seen in Fig. 11(d).

Numerically speaking, the performance of the proposed method is very satisfying. The statistical results presented in Table 1 illustrate that for the images in the CASIA-Iris V3, the proposed method leads with a high success rate while the Canny-based segmentation method trails with a slight difference. For the images in the the UBIRIS.V1, due to the poor quality of the images and the precision of the proposed method in eliminating the noise pixels in the edge map, the proposed method outperforms the Canny-based segmentation method with a lager gap. The Sobel-based segmentation method does not show a desirable efficiency in either of the cases.

6. Conclusion

A new iris segmentation method that takes advantage of a robust edge detector has been proposed. Because of the accuracy of the edge detector, the segmentation method performs efficiently on images acquired nonideally and in uncontrolled environments, which can be categorized as noisy. The proposed method consists of a new edge detector and Hough transform. The approach is designed with the assumption that all the pupils and irides are circular, which in actuality are not. However, in comparison with previous methods based on the same assumption, the proposed method presents much more satisfying results.

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