Iris Localization and Recognition Using Second Gradient Norm Features

Iman A. Saad, and Loay E. George

Abstract—Iris is regarded as the most reliable and accurate biometric identification system available. In this paper, we propose a novel system for iris recognition composed of image preprocessing including (segmentation, normalization, eyelashes and eyelids detection, enhancement), features extraction and classifier design. Iris feature extraction is based on using second order gradient images operator that will be robust against the variations may occur in iris’s contrast or illumination because of lightening differences and camera changes. The low order norms of gradient components are used to establish the feature vector. The experimental results indicated that the efficiency of our proposed method when tested on the CASIA v1 and CASIA v4-Interval database is promising, it achieves nearly perfect high recognition rate.

Keywords—Iris recognition, contrast stretching, gradient features, Euclidean classifiers.

I. INTRODUCTION

NOWADAYS iris recognition is playing more important role in many mission-critical application, such as access control, personal identification, border crossing, E-passport, etc. The purpose of “Iris Recognition” is to recognize a person from his/her iris prints [1]. The created iris patterns of human are largely completed at the eighth month after his porn. Pigment accretion can continue into the first postnatal year. Formation of unique iris patterns is random and not related to any genetic factor. Due to the epigenetic nature of iris, two eyes of an individual contain completely independent iris patterns (see Fig. 1).

Fig. 1 Distinctiveness of the right (S1097R03) and left (S1097L03) eyes taken form CASIA v4-Interval database.

Iris has unique features and highly complex patterns to be used as a biometric [2], [3]. Therefore, the iris recognition systems are very reliable and could be used in most secure places [4]. The state-of-art of iris recognition was done by Daugman; he used Gabor filters to demodulate texture phase structure information of the iris [5]. That system had been widely implemented and tested by many researchers. Wildes [1], [6] then used the gradient criterion and circular Hough transform to locate the iris. Besides, he proposed the application of Laplasian operator to extract the iris images features in 4 levels of accuracy (i.e., Laplasian with 4 different resolution levels) and used the normalized correlation coefficients for matching between the patterns of images. Boles and Boashash proposed a novel iris recognition algorithm based on zero crossing detection of the wavelet transform, this method has only obtained the limited results in the small samples, and this algorithm is sensitive to the gray value changes, thus recognition rate is lower [7], [8]. Proposed a set of local and global properties of an iris image for establishing iris feature vector. However, many issues, including system robustness, speed of enrolment and recognition remain to be addressed. Since the distinctive iris’s pattern information is preserved in the randomly distributed micro textures, formed by many fiber, contraction furrows, coronas, freckles, rifts, crypts and pits, it is noticed that the distinctiveness of an iris pattern relies on the statistical features of image sub-regions (blocks) and all sub-regions are used to construct a local texture features. The performance of iris recognition system depends on the good image quality and extremely clear iris texture details, so noisy and low quality image degrade the performance of the system. In this paper, a robust iris recognition system is introduced to deal with bad quality image, low contrast and brightness variation, bad lighting, and occlusion by eyelids and eyelash and inappropriate eye position; and to gain high recognition performance.

II. METHODOLOGY

The proposed iris recognition system consists mainly of seven stages; (1) Segmentation, (2) Normalization, (3) Eyelashes and Eyelids Detection, (4) Enhancement, (5) Features Extraction, (6) Generate Features Templates, (7) Iris Identification. These stages are described in the following sub-sections.

2.1 Iris Segmentation

Iris segmentation is the process that is done to localize and extract the iris region from the other parts of the eye image. In our earlier method described in [9], a fast and accurate algorithm for detecting the boundaries between pupil and iris
and between sclera and iris had been proposed. Original iris images may have low contrast and non-uniform illumination, caused by the position of the light source and this will impair the iris segmentation’s process. Therefore, before applying the extraction process, the iris image must be enhanced in order to get an image with uniformly distributed brightness and have better contrast; this brightness-contrast condition is handled by means of linear contrast stretching to bring the iris image into intensity range that is more normal or suitable to be segmented accurately. This iris enhancement step is just for segmentation purpose. The introduced Iris boundaries localization algorithm implies the following steps:

A. Allocate the iris inner boundary: By determining the pupil geometrical parameters (i.e., center point coordinates & radius) from the enhanced iris image.

B. Allocate the iris outer boundary; the introduced method is based on using Leading Edge Detection method [9].

Fig. 2 shows samples of the detected iris regions when our developed method is applied on CASIA v1 and CASIA v4 images. The attained accuracy rate for localizing both the inner and outer iris boundaries as circles shape was 100% for both CASIA v1 and CASIA v4-interval database images.

![Fig. 2 Iris localization. (a) Samples from CASIA v1. (b) Samples from CASIA v4-interval database](image)

2.2 Iris Normalization

The captured iris images can have different sizes; this variation is due to pupil dilation caused by varying levels of illumination, rotation of the eye and other factors. The normalization process will produce iris regions, which have the same constant dimensions. So, once the iris region is localized from the previous stage, the iris should be normalized and mapped to change the iris shape from circular to rectangular form. The size normalization and shape conversion is accomplished by unwrapping the iris region and map all the points lay between the iris boundaries from the original Cartesian coordinates \( I(x,y) \) into their equivalent normalized polar coordinates \( I(r,\theta) \) using the following mapping equation:

\[
I(x(r,\theta),y(r, \theta)) \rightarrow I(r, \theta)
\]

Where, \( r \in [R_P, R_I]; R_P \) is the Pupil’s radius, \( R_I \) is iris’s radius and \( \theta \) is angle \( [0^\circ, 360^\circ] \), (see Fig. 3).

![Fig. 3 Illustration of size normalization and mapping to rectangular shape of the iris region](image)

The iris region is resembled to a rectangle of \((h \times w)\) pixels through making \((h)\) samplings along radial \((r)\) direction, and making \((w)\) samplings along the whole angle \(\theta\) range (i.e., \([0, 360]\)), as shown in Fig. 4. The equations of applied normalization are the following:

\[
x = X_P + r \ Sin (\theta)
\]

\[
y= Y_P - r \ Cos (\theta)
\]

\[
\text{Normalize}_\text{Iris} (i, j) = I(y, x)
\]

Where, \( i = 0,1,2,...,h \), \( j = 0,1,2,...,w; P(X_P,Y_P) \) is the pupil’s center and \( \theta = j \times (\pi /180) \).

![Fig. 4 Sample of normalization process output](image)

In the conducted experiments, the size of the rectangular iris image is set \((60, 360)\) pixels. Only the iris portion located under the upper dotted line (see Fig. 4), was used to provide iris texture signature (i.e., features vector) for recognition purpose, the region lay above the upper dotted line mostly contains some pixels of pupil region because the pupil region is not perfectly circular.

2.3 Eyelashes and Eyelids Detection

Usually, in the iris image area the overlapped eyelashes points appear dark (as black) pixels, and they may locate at the upper and lower side of the image; while the overlapped eyelid points appear bright (as white) pixels. Also, it may appear at the upper and lower sides of the iris image. In this paper a method is proposed to detect the eyelid and eyelashes pixels, it consists of the following main stages:

2.3.1 Generate an Initial Mask

The mask initialization is the important step to detect eyelash and eyelid as noisy points. The initial mask consists only of two regions: one taking as a noisy (=0) and the other as the iris (=1) through applying linear contrast stretching upon the iris image; this will shift the lowest existing gray level value toward 0, and the highest gray toward 255. To ensure making this mapping process lead to stable eyelashes and eyelids detection performance, the lowest and highest gray
level component values are assessed according to the following statistical bases:

\[ V_{\text{lowest}} = M - \alpha \sigma \]  
\[ V_{\text{highest}} = M + \alpha \sigma \]  

Where \( V_{\text{lowest}} \) and \( V_{\text{highest}} \) are the assessed values for the lowest and highest gray levels values for the iris pixels, \( M \) is the mean value for the image gray levels; \( \sigma \) is the corresponding standard deviation value and \( \alpha \) is a predefined parameters used to control the strength of the stretching parameter, its value should be within the range \([1,3]\). Then, the linear contrast stretching is done by applying the following mapping equation:

\[
I_{\text{str}}(x,y) = \begin{cases} 
0 & \text{if } I(x,y) < l_{\text{lowest}} \text{ or } l(x,y) > l_{\text{highest}} \\
255 \frac{(l(x,y) - l_{\text{lowest}})}{(l_{\text{highest}} - l_{\text{lowest}})} & \text{if } l_{\text{lowest}} \leq l(x,y) \leq l_{\text{highest}} 
\end{cases}
\]  

Where, \( l_{\text{str}}(x,y) \) is the image after applying contrast stretching, and \( I(x,y) \) is the original image.

2.3.2 Apply Dilation and Erosion

Dilation and erosion are the most basic morphological operations. Both dilation and erosion are produced by moving a structuring element around the image. Based on the image that to be dilated or eroded the size of the structuring element is chosen, it is odd square matrix which contains binary elements (i.e., 0’s and 1’s). After the step of marking the nominated eyelids and eyelashes as black points, it can be noticed that some small clumps of noise points (0’s) appears in the produced binary iris image, so dilation operation is used to remove these noise points from the iris region through replacing the mark of false assigned noise pixels to foreground pixel. Erosion is used to eliminate small clumps of iris points that appear in the noise region.

2.3.3 Apply Seed Fill Algorithm

Perhaps the established iris mask may contain patches of noisy points (0’s) appear in the region of interest (iris), so the use of seed fill algorithm removes such patches by checking the value of the mask’s pixels to the right, left, down and up of the current pixel, and it changes any noise pixel value belong to the collected small patch from zero to one.

2.4 Iris Enhancement

Normalized iris image should be enhanced before features extraction. The normalized images are directly extracted from the original images which may have low contrast and may have non uniform brightness due to the changes in position of light sources; these two low-quality defects may significantly affect the outcomes of feature extraction and matching processes. Therefore, contrast stretching is adopted to enhance the normalized iris image and to get images have same overall brightness (DC-energy) and contrast (AC-energy). The purpose of contrast stretching is to bring the iris image into an intensity range that is more normal or suitable for features extraction phase.

At first, the mean \( M \) and standard deviation \( \sigma \) of the normalized image are computed using the following equations:

\[
M = \frac{1}{LxW} \sum_{i=0}^{255} i \times \text{Hist}(i)
\]  

Where, \( LxW \) is the image size, \( \text{Hist}(i) \) is the total number of pixels have \( i \) gray level value.

\[
\sigma = \frac{1}{LxW} \sum_{i=0}^{255} (i - M)^2 \times \text{Hist}(i)
\]  

The applied mapping function for contrast stretching was done using the following equation:

\[
G'(x,y) = \frac{255}{\sigma} (G(x,y) - M) + 128
\]  

Where, \( G(x,y) \) is the pixel’s intensity and \( G'(x,y) \) is the mapped pixel value. The suitable value of \( A \) parameter is assessed by testing. A sample of the enhancement process is shown in Fig. 5, the mapping function maps the lowest found gray level in the image to zero and the highest gray level to 255, the other gray levels are mapped linearly between 0 and 255.

Fig. 5 Sample of Enhancement Process Results

2.5 Features Extraction

Every iris image has distinctive features that make it distinguishable from other. So, good iris features should have high discrimination power in terms of identifying the iris images. In this paper, a new set of texture features is proposed depending on using the second order gradient images operator. As shown in Fig. 6 the differences in the shapes of 1st and 2nd gradient operators outputs indicate capability of both outputs to describe the iris signature in different manner, beside to that the outcomes of gradient operators are less sensitive to variations in brightness of the image.
2.5.1 Application of Local Gradient Operators

Gradient operator measures the directional change of the pixel value; just like the first order gradient the second order gradient (i.e., 2nd degree of intensity change measure) captures the local textural behavior of the iris signal. Each element of the outputs of gradient operators represents the change in intensity, along specific direction, at certain position in the original image. The taken gradient operators \(G\) are following:

\[
G = \left\{ \frac{\partial^2 f}{\partial x^2}, \frac{\partial^2 f}{\partial y^2}, \frac{\partial^2 f}{\partial x \partial y} \right\}
\]  

(11)

Where, \(\frac{\partial^2 f}{\partial x^2}\) is the gradient along the horizontal direction, \(\frac{\partial^2 f}{\partial y^2}\) is the gradient along the vertical direction, \(\frac{\partial^2 f}{\partial x \partial y}\) is the gradient along both directions \(x\) & \(y\). The gradient arrays are computed according to the following equations:

\[
G_{XX}(x, y) = 2P(x, y) - P(x+1, y) - P(x, y+1) + P(x+1, y+1) 
\]  

(12)

\[
G_{YY}(x, y) = 2P(x, y) - P(x+1, y) + P(x, y+1) - P(x+1, y+1) 
\]  

(13)

\[
G_{DD}(x, y) = 2P(x, y) - P(x-1, y-1) - P(x+1, y+1) + P(x-1, y+1) 
\]  

(14)

\[
G_{XY}(x, y) = P(x, y) + P(x+1, y) - P(x+1, y+1) - P(x, y+1) 
\]  

(15)

\[
G_{YX}(x, y) = P(x, y) + P(x, y+1) - P(x+1, y+1) - P(x+1, y) 
\]  

(16)

\[
G_{D2}(x, y) = P(x, y) + P(x+1, y) + P(x, y+1) + P(x+1, y+1) 
\]  

(17)

The \(G_{XY}\) is the horizontal gradient of the vertical sum of iris pixels; \(G_{YX}\) is the vertical gradient of the horizontal sum; \(G_{D2}\) is the gradient of the diagonal sums. Actually the operators \(G_{XX}, G_{YY}\) and \(G_{DD}\) are first order gradients but combined with mean operator. They added to the proposed second order set \((G_{XX}, G_{YY}, \text{and } G_{DD})\) in order to investigate their discrimination powers. Fig. 7 shows examples of the gradient images. Eventually, any pixel that has large gradient value, along any direction, is an edge pixel.

2.5.2 Image Partitioning (Blocking) with Overlapping

To address the local iris signature, each obtained gradient image is divided into overlapped blocks with certain overlapping ratio \(O_{\text{Ratio}}\) along the horizontal \((x)\) and vertical \((y)\) directions, as shown in Fig. 8. The proper numbers of blocks along the vertical \((N_y)\) and horizontal \((N_x)\) directions and the overlapping ratio values have been searched by testing various combinations of values to find the best setup that leads to best recognition rate. Then, the blocks’ dimensions \((H_{\text{block}}, W_{\text{block}})\) in both directions are determined, since the width and height of the normalized image are not equal, so the blocks dimensions (i.e., height and width) are not equal.

2.5.3 Determination of Block Weight

After partitioning the gradient image into overlapped blocks; these blocks are categorized to be between the two extreme classes: (i) iris blocks, (ii) noisy blocks. The categorization is done by applying the following criterion:

\[
F = D_{\text{Rand}}(\mu - t) 
\]

(18)

\[
w(\mu) = \frac{1}{1 + \exp(F)} 
\]

(19)

The suitable value of \(D_{\text{Rand}}\) and \(t\) parameters are assessed by testing; where, \(\mu\) is the ratio of total numbers of flagged noise pixels (eyelash and eyelid) relative to the block size; the value of block decision weight \(w(\mu)\) should be between the range \([0, 1]\). Fig. 9 presents three different iris blocks taken from different iris regions.

2.5.4 Determination of Gradient Density

The density (norms) is calculated for each iris block separately, and then they assembled in one features vector to be treated as a signature vector for the iris image. The values of the norm gradient density are calculated as iris features, the values are determined using the following equations:

\[
M_{GC}(m) = \frac{1}{N_{\text{iris}} \times \text{pix} 	imes \text{y}} \sum_{\text{pix} \times \text{y} \times \text{block}} \|G_{(x, y)}\|^m 
\]

(20)

\[
M_{GS}^{s}(m) = \frac{1}{N_{\text{iris}} \times \text{pix} \times \text{y} \times \text{block}} \sum_{\text{pix} \times \text{y} \times \text{block}} \|\text{sign}(G_{(x, y)})\|^m 
\]

(21)

Where \(G_{(x, y)}\) is either \(G_{XX}, G_{YY}, G_{DD}, G_{XY}, G_{YX}\) or \(G_{D2}\), \(N_{\text{iris}}\) is the number of iris points \((p)\) belong to the block \((N_{\text{iris}} = H_{\text{block}} \times W_{\text{block}})\). Fig. 9 Examples of three iris blocks taken from different iris regions (the block surrounded by red frame is purely iris, the region surrounding by cyan frame is partially contaminated, and the block surrounded by yellow frame is completely contaminated).

Mostly, the iris blocks located at middle region and nearest pupil take high weight values because these regions are less affected by the noisy points of eyelashes and eyelids.
2.6 Generation of Features Templates

Before starting the matching process, the template feature vector $T$ for each class (person) should be determined and registered in a database. For computing the template vectors for each class, the mean and standard deviation vectors for the feature vectors extracted from different image samples belong to one class are determined using the following equations:

$$\text{Mean}(f,c) = \frac{1}{\text{NoSmp}} \sum_{s=1}^{\text{NoSmp}} \text{Feature}(f,c,s)$$  \hspace{1cm} (22)

$$\text{Sd}(f,c) = \frac{1}{\text{NoSmp}} \sum_{i=1}^{\text{NoSmp}} (\text{Feature}(f,c,s) - \text{Mean}(f,c))^2$$  \hspace{1cm} (23)

Where, the indices $f \in \{1, \text{NoFeatures}\}$, $c \in \{1, \text{NoClasses}\}$, $s \in \{1, \text{NoSamples}\}$; NoSmp is the number of training samples for each class.

The adopted mechanism to handle the features analysis task was aimed to find out the lowest possible combination of features that can lead to good iris recognition results; the recognition accuracy was evaluated using the following measure:

$$\text{Success Rate} = \frac{\text{No.of Successful Hits}}{\text{Total No.of Recognition Tests}}$$  \hspace{1cm} (24)

In this work, the recognition accuracies for all features combinations have been tested. The tests started with single features (i.e., every feature is tested alone), then the number of features was expanded to pair of features, then to combination of triple features and more.

Then, the mean value (i.e., template value) and its associated standard deviation value for each feature belong to the successful discriminating combinations are calculated for all classes, and the values are stored in a dedicated database.

2.7 Iris Identification (Matching)

Iris recognition based on given features vectors is a typical pattern recognition problem. The template which is created from previous phase should be used for matching purpose. The used similarity measure to match the features vectors is the weighted Euclidean distance metric [10]. The features extracted from the unknown iris samples compared with the corresponding features belong to the registered templates in the database. The tested iris is identified as belong to subject $m$ if the weighted Euclidean distance with template $m$ is the lowest one. Euclidian distance measure is expressed mathematically as follows:

$$\text{WED}(S,T_i) = \sqrt{\sum_{k=1}^{\text{Total number of blocks}} \left(\frac{S(i,k) - T(j,k)}{T(j,\sigma(k))}\right)^2}$$  \hspace{1cm} (25)

Where, $S(i,k)$ denotes the value of $k^{th}$ feature extracted from unknown $i^{th}$ sample; and $T(j,k)$, $T(j,\sigma(k))$ are the template value of $k^{th}$ feature belong to $j^{th}$ class and the corresponding standard deviation.

### III. RESULTS AND DISCUSSION

The performance of the proposed iris recognition has been tested on the CASIA v1 database; which includes 756 images belong to 108 classes, for each class there are seven iris images captured in two sessions. Also, the system was applied on CASIA v4-interval database; it consists of 2639 iris images captured from 249 subjects. The right iris images are 1332 images taken from 198 different subjects (the other 51 classes do not have any sample of right iris). While the left iris images are 1307 images belong to 197 subjects. One of the most important properties of iris, which makes it a wonderful biometric identification technology, is the "genetic independence"; i.e., iris not only differ between identical twins, but also between the left and right eye, so, in our conducted tests we have considered right and left iris as different classes belong to the same person (subject), so, the total number of classes will be 395 and number of processed images is 2639 images. Many researchers have applied the feature extraction stage only upon the iris images which are correctly segmented and have sufficient texture information for recognition, while in our study the conducted tests have been applied on the whole CASIA v1 and CASIA v4-interval database images because the attained accuracy rate by our method for iris segmentation was 100%.

The recognition system performance is affected by a number of parameters, so it is a pre-requisite to choose the optimum values for these parameters to improve the efficiency of recognition system. The suitable parameters values that led to highest successful recognition rates are shown in Table I.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Optimum Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$O_{awa}$</td>
<td>0.1</td>
</tr>
<tr>
<td>$h_{block}$</td>
<td>14</td>
</tr>
<tr>
<td>$w_{block}$</td>
<td>45</td>
</tr>
<tr>
<td>Image height</td>
<td>60</td>
</tr>
<tr>
<td>Image width</td>
<td>360</td>
</tr>
<tr>
<td>$N_x$</td>
<td>8</td>
</tr>
<tr>
<td>$N_y$</td>
<td>4</td>
</tr>
<tr>
<td>Total number of blocks</td>
<td>32</td>
</tr>
<tr>
<td>$A$</td>
<td>100</td>
</tr>
<tr>
<td>$D_{raw}$</td>
<td>20</td>
</tr>
<tr>
<td>$T$</td>
<td>0.6</td>
</tr>
</tbody>
</table>

The identification results for different types of features are listed in Table II; it shows the attained recognition success rates for CASIA v1 database, when only single, double, third features are used for representing each iris block from total 32 blocks. The best recognition rate for combinations of three features {[M$_{GYX}$0.5], [M$_{GXY}$0.5], M$_{GYX}$0.5]} was (100%).
The developed iris recognition system on a computer platform was tested and found to achieve an accuracy of 99.96%. The test results were obtained by running the system on a computer with a 2.4 GHz Core i5 processor, 2 GB RAM, and Windows-7 operating system. Six CASIA v1 database images were used for testing, and the results showed that the highest attained recognition percentage for the complete CASIA v4-interval database images was 99.96%. It was found that using only one feature for representing each iris block for iris segmentation improves the efficiency of each stage, thereby reducing the time needed for processing and matching.

Table III shows the best attained recognition rates when using only one feature for representing each iris block for the samples belonging to CASIA v4 interval-Database images. Also, the table shows the best recognition rates when combinations consist of two, three up to five features are used for representing each iris block.

Table III: Recognition Rates for CASIA V1 Database

<table>
<thead>
<tr>
<th>No. of Features</th>
<th>Features Type</th>
<th>Recognition Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M(Gxy)(0.5)</td>
<td>96.56</td>
</tr>
<tr>
<td>2</td>
<td>M(Gxy)(0.5), M(Gxd)(0.5)</td>
<td>99.74</td>
</tr>
<tr>
<td>3</td>
<td>M(Gxy)(0.5), M(Gxd)(0.5), M(Gxd)(0.5)</td>
<td>100</td>
</tr>
</tbody>
</table>

From the results shown in Table III, it is found that combinations of four features { M(Gxy)(0.5), M(Gxy)(0.5), M(Gxy)(0.5), M(Gxd)(0.5) } could lead to the highest recognition accuracy (99.96%). The test results were obtained by running the developed iris recognition system on a computer platform with 2.4 GHz Core i5 processor, 2 GB RAM, and Windows-7 OS platform. The programs were developed using Visual Basic-6 programming language.

IV. CONCLUSIONS

In this paper, a novel method is proposed for iris recognition; it extracts the distinctive iris features based on the second order gradient operators which are less susceptible to lighting, contrast and camera changes. For iris segmentation, we have used our proposed method that mentioned in [9] which gives segmentation efficiency 100%. Then, scaling and mapping operations have been carried out to produce a rectangular iris image that has a size (60 x 360 pixels). From the listed tables it can be concluded that using the second order gradient operator for iris signature formation gives reliable results up to 100% recognition rate for whole CASIA v1 database images while for complete CASIA v4-interval database images, the highest attained recognition percentage arrived to 99.96%. Also, it is found that:

- Assigning a decision weight for each block is important because some of the iris blocks are noise free while other blocks are mainly populated by noise points. The use of weight improves recognition accuracy because the free-noise blocks will participate more than noisy blocks in the decision metric.

- Using weighted Euclidean distance as a distance measure provides a good way to test the strength of the feature vector(s) and it is required to assess the capability of recognizing and identifying persons.

- The adopted mechanism to handle the feature analysis task was aimed to find out the lowest possible combinations of features that can lead to good texture recognition results. The size of features combination was gradually increased and at each test step the best sets of features which can give the highest recognition rate found. In this paper, the sets of features combination started with single feature and gradually expanded to a pair of features, and then to a set consist of triple and so on till fourth or fifth.

- Second order gradient operator applied on grayscale images proved to be good generator for iris texture descriptors; because they determine the local directional variations along the iris image area.

- The conducted test results indicate that discrimination power of low order norms (0.5) is the highest one, and it is very useful for iris recognition task.

- The set of best features that represent each iris block consists of three features for CASIA v1 and just four features for CASIA v4 from the total 30 features; this will reduce the time needed for processing and matching.

- The proposed method gives promising results; and this proves the accuracy of each system stage because the efficiency of each stage affects the overall accuracy of recognition rates.

REFERENCES