A Survey: Feature Extraction Methods for Iris Recognition

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Abstract—The biometrics is the study of physical traits or behavioral characteristics of human include items such as fingerprints, face, hand geometry, gait, keystrokes, voice and iris. Among the biometrics, iris has highly accurate and reliable characteristics. An iris has unique structure and it remains stable over a person life time. Iris recognition is one of the biometric identification and authentication that employs pattern recognition technology with the help of high resolution. A general approach of iris recognition system includes image acquisition, segmentation, feature extraction, matching/classification. The performance of biometric system based on iris recognition depends on the selection of iris features. In this work performance of various feature extraction methods are analyzed for iris recognition.

Keywords- Hough Transform; Iris Normalization; Pattern Matching; Feature Extraction.

I. INTRODUCTION

Iris recognition is a method of biometric authentication that uses pattern-recognition techniques based on high resolution images of the irises of an individual's eyes [1]. The human iris, an annular part between the pupil (generally, appearing black in an image) and the white sclera has an extraordinary structure and provides many interlacing minute characteristics such as freckles, coronas, stripes, etc. These visible characteristics, which are generally called the texture of the iris, are unique. While most biometric have 13 to 60 distinct characteristics, the iris is said to have 266 unique spots. Each eye is believed to be unique and remain stable over time.

A. Basic steps in iris recognition:

The first step, image acquisition deals with capturing sequence of iris images from the subject using cameras and sensors. These images should clearly show the entire eye especially iris and pupil part, and then some preprocessing operation may be applied to enhance the quality of image e.g. histogram equalization, filtering noise removal etc. The next step of iris recognition is to isolate the iris portion from the eye image, called segmentation. It is a technique required to isolate and exclude the artifacts as well as locating the circular iris region. The inner and the outer boundaries of the iris are calculated. Segmentation of iris depends on the quality of the eye images. An automatic segmentation algorithm based on the circular Hough transform is employed by Wildes et al. [2], Kong and Zhang [3], Tisse et al. [4], and Ma et al. [5].

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In third step segmented iris is normalized. The normalization process will produce iris regions, which have the same constant dimensions, so that two images of the same iris under different conditions will have characteristic features at the same spatial location.

In order to provide accurate recognition of individuals, the most discriminating information present in an iris pattern must be extracted in the fourth step. Only the significant features of the iris must be encoded so that comparisons between templates can be made. This paper is mainly study of different feature extraction algorithms available.
Once the features of iris are extracted we are required to match the iris template with the available in the database. Most of the authors have calculated Hamming distance [6,7] between two iris template. The Hamming distance algorithm employed, also incorporates noise masking, so that only significant bits are used in calculating the Hamming distance between two iris templates.

![A view of human eye](image)

Figure 2. A view of human eye

In this paper, a survey on different feature extraction algorithms is made. In the next section we will discuss the feature encoding using corner detection. Haar wavelet based feature extraction algorithm is discussed in the next section, followed by encoding with Gabor filter and at the last Fast Fourier Transform based statistical pattern recognition model is discussed. Then result analyses of various feature extraction methods are discussed.

II. FEATURE EXTRACTION METHODS

A. Corner Detection Based Iris Encoding

In this approach authors presented an iris recognition algorithm using corner detection [8]. Here image is acquired by 3CCD camera so that image is of very good quality because iris texture is used as feature to be extracted. The approximate distance between the user and the source of light is about 12 cm. then in localization step involved two sub steps, pupil detection followed by outer iris localization. The basic idea of this technique is to find curves that can be parameterized like straight lines, polynomials, circles, etc., in a suitable parameter space. In the first step author finds intensity image gradient at all the locations in the given image by convolving with the sobel filters. The gradient images (G_{vertical} and G_{horizontal}) along x and y direction, is obtained by kernels that detect horizontal and vertical changes in the image. The sobel filter kernels are

\[
C_{vertical} = [-1 -2 -1; 0 0 0; 1 2 1] \\
C_{horizontal} = [-1 0 1; -2 0 2; -1 0 1]
\]

(1)

The absolute value of the gradient images along the vertical and horizontal direction is obtained by kernels that detect horizontal and vertical changes in the image. The image gradient is given by

\[
G_{abs} = G_{vertical} + G_{horizontal}
\]

(2)

Where, G_{vertical} is the convolution of image with C_{vertical} and G_{horizontal} is the convolution of image with C_{horizontal}. The absolute gradient image is used to find edges using Canny [9]. The edge image is scanned for pixel (P) having true value and the center is determined with the help of the following equations

\[
xc = x - r \times \cos(\theta) \\
yc = y - r \times \sin(\theta)
\]

(3)

Where, x and y are the coordinates at pixel P and r is the possible range of radius values ranges from [0: π]. For a particular value of r, the values of xc and yc are obtained and stored in an accumulator and the accumulator counter is incremented every time the values of xc and yc satisfy image dimension criteria. The maximum value of accumulator counter gives the centre of the pupil along with the radius as shown in Fig. 3.

![Steps involved in detection of inner pupil boundary](image)

Figure 3. Steps involved in detection of inner pupil boundary

In second step older iris portion is localized. External noise is removed by blurring the intensity image. But too much blurring may dilate the boundaries of the edge or may make it difficult to detect the outer iris boundary, separating the eyeball and sclera. Then normalization step employs the concept of rubber sheet modal suggested by Daugman. The coordinate system is changed by unwrapping the iris and mapping all the points within the boundary of the iris into their polar equivalent as shown in Fig. 4. The mapped image has 80 x 360 pixels. It means that the step size is same at every angle. Therefore, if the pupil dilates the same points are picked up and mapped again which makes the mapping process stretch invariant.

![Iris normalization](image)

Figure 4. Iris normalization

Gupta et al. [8] have presented following feature extraction algorithm using the corner detection:

Step 1: The normalized iris image is used to detect corners using covariance matrix.

Step 2: The detected corners between the database and query image are used to find cross correlation coefficient.

Step 3: If the number of correlation coefficients between the detected corners of the two images is greater than a threshold value then the candidate is accepted by the system.

A Covariance matrix of changing intensities at each point is used to detect corner points. A 3x3 window centered on point p is considered to find covariance matrix \( M_p \),

\[
M_p = \begin{bmatrix}
\sum D_x^2 & \sum D_x D_y \\
\sum D_x D_y & \sum D_y^2
\end{bmatrix}
\]

(5)
Where $Dv$ is the change in intensity along columns and $Dr$ is the change in intensity along rows. The summation is done over 3x3 window. If eigenvalue of $Mw$ is greater than a threshold it is considered as a corner. The corners are detected after removing the eyelids from the normalized iris image. The result of corner detection is shown in Fig. 5.

$$
C_{ij} = \frac{\sum_{u} \sum_{v} (A_{uv} - A_{avg})(B_{uv} - B_{avg})}{W^2 \cdot \sigma(A) \cdot \sigma(B)}
$$

From the experimental results it is found that the recognition system is showing an overall accuracy of 95.4 % with FRR of 5% and FAR 4%.

B. Feature extraction using Haar wavelet

Singh et al. [6] calculated the features of the iris using Haar wavelet transform for recognition. Authors compared the results using Haar transform with the wavelet tree obtained using other wavelets and found slightly better results. Authors obtained the five level wavelet tree showing all detail and approximation coefficients using Haar wavelet.

These levels are $cD_1^h$ to $cD_5^h$ (horizontal coefficients), $cD_1^v$ to $cD_5^v$ (vertical coefficients) and $cD_1^d$ to $cD_5^d$ (diagonal coefficients). Then the coefficients that represent the core of the iris pattern are chosen, and those consist redundant information are eliminated. Figure 6 is showing the wavelet transform of iris image up to five level and we can see that patterns in $cD_1$, $cD_2$, $cD_3$ and $cD_4$ are almost the same so only one of them may be chosen to reduce redundancy. Since $cD_2$ repeats the same patterns as the previous horizontal detail levels and it is the smallest in size, then we can take it as a representative of all the information the four levels carry. The fifth level does not contain the same textures and should be selected as a whole. In a similar fashion, only the fourth and fifth vertical and diagonal coefficients can be taken to express the characteristic patterns in the iris-mapped image. Thus it can represent each image applied to the Haar wavelet as the combination of six matrices:

1. $cD_1^h$ and $cD_1^v$
2. $cD_1^v$ and $cD_3^v$
3. $cD_1^d$ and $cD_3^d$

All these matrices are combined to build one single vector characterizing the iris patterns. This vector is called the feature vector [10]. All mapped image is fixed size then all image will have a fixed feature vector. This vector has a size of 702 elements. This means that it is managed to successfully reduce the feature vector of Daugman who uses a vector of 1024 elements [11]. This difference can be explained by the fact that we always maps the whole iris even if some part is occluded by the eyelashes, while in this paper mapping is done only the lower part of the iris obtaining almost half his feature vector’s size. Then a binary coding of the obtained feature vector. Since it is easier to find the difference between two binary code-words than between two number vectors. All the vectors that is obtained have a maximum value that is greater than 0 and a minimum value that is less than 0. Moreover, the mean of all vectors varied slightly between -0.08 and -0.007 while the standard variation ranged between 0.35 and 0.5.

If “Coef” is the feature vector of an image than the following quantization scheme converts it to its equivalent code-word:

- If $\text{Coef}(i) > 0$ then $\text{Coef}(i) = 1$
- If $\text{Coef}(i) < 0$ then $\text{Coef}(i) = 0$

In the next step there is a comparison of two code-words to find out if they represent the same person or not. Hamming distance between two binary code is calculated to make a decision. The work have 60 pictures, on which test is conducted and obtained an average of correct recognition of 95%, with an average computing time of 23 secs.

C. Feature extraction using Gabor filter

Tuama [12] extracted the features of the normalized iris by filtering the normalized iris region. This filtering is performed by convolution with a pair of Gabor filters. Information about noise position in this stage are also extracted and stored. So, the iris code [13] is formed by some characteristic information extracted from normalized iris
filtered by convolution (a pair of resulting images) and a Boolean mask representing the position of noisy pixels.

A Gabor filter is a sine (or cosine) wave modulated by a Gaussian (see fig. 8). This kind of filters optimally extracts information in space as well as in frequency domain. To extract iris features we designed two Gabor filters. First filter is a sine wave modulated by a Gaussian. Second is the same as first but using a cosine wave. In these filters, the central frequency of the filter is specified by the sine (or cosine) wave frequency and bandwidth varies as Gaussian width does. At implementation level, each filter must be a matrix [14].

Each Gabor wave must be in a discrete form. To get this, authors have only applied the two functions, sine and Gauss (or the composition of the two) on a discrete space, for example, the elements of a matrix.

\[ y(r,s) = \sum_{p=0}^{P} \sum_{q=0}^{Q} h(p,q) \star x(r-p,s-q) \]

Where \( x(r,s) \) is the discrete input signal (input image), \( h(p,q) \) is the convolution kernel, with dimensions \( P \times Q \), and \( y(r,s) \) is the filtered output signal, with same size as input.

Author used 1-D vectors instead of matrices. Given a normalized image, each row of pixels is taken as an input signal and is filtered by the one dimensional Gabor function. Each of these one dimensional vectors is a cross cut of the two-dimensional corresponding matrix. At implementation level, it is only have to calculate the central row of Gabor matrix. One dimensional filter notably speeds up filtering process because much less operations are needed to perform the convolution. Moreover, it has experimentally concluded that accuracy of the whole system is unaffected when using one-dimensional kernels instead of two dimensional ones. Filtered image is not taken as the process output. The output signal’s sign is more characteristic than its value. An output pixel value is positive or negative due to its own value and the value of its neighbor pixels. An output pixel value is lower or greater depending on other image factors like bright or contrast and thereby more susceptible to change when input image conditions change. Therefore, after filtering, each image is threshold in order to get the final iris code.

In next step matching and identification is done. In the matching process, the extracted features of the iris are compared with the iris images in database. If enough similarity is found, the subject is then identified.

!!Figure 8. Gabor filter generation: (a) A sine wave. (b) A Gaussian. (c) The sine wave modulated by the Gaussian.!!

**D. Statistical pattern recognition**

In this work[14] Fast Fourier transform is used to extract the features. A test is conducted and it is found that mid-to-high frequencies are the most important features in classification. Upon first glance of an iris, the mid-to-higher frequency content appears to be concentrated near the boundary of the pupil. An FFT of the individual samples was then taken and the mid-to-high spectral bands were averaged to produce the results. The spikes on the outer bands are largely due to the interfering eyelids. With this in mind, logarithmic feature extraction techniques were used in early tests of the system.

Data is sampled from the iris by starting at the pupil boundary and expanding outwards in a log spiral to the sclera boundary. The log spiral is defined in Cartesian form as:

\[ x = r_{pupil} \exp(a \theta) \cos \theta \quad \text{Where} \]

\[ 0 \leq \theta \leq 2 \pi \ast \text{Numspiral} \]

\[ y = r_{pupil} \exp(a \theta) \sin \theta \quad \text{Where} \]

\[ a = \frac{\log(r_{sclera}/r_{pupil})}{2 \pi \ast \text{Numspiral}} \]

Advantages of log spiral are as follows

a. Reduces the dataset from two to one dimensional space.

b. Eliminates discontinuities in data caused by sampling with circles.

c. Concentrates on the higher frequency content of the inner iris.

d. Reduces the likelihood of invalid eyelid and eyelash data.

The high frequency transitions from iris to eyelid/eyelash made the outer portion of the iris just as important as the inner iris as long as the test image had a similar level of iris visibility as the training image. In a more expressive system, the eyelids and eyelashes would have been removed from the iris map and not accounted for in the model. Data is sampled in the final system by taking the brightness levels in 50 pixel intervals along the concentric circles (with 50% overlap).

After applying the Hamming Window, a Fast Fourier Transform is evaluated on the resulting data.

**E. Multichannel Gabor Filter**

The 2-D Gabor filters have been used in image processing for feature extraction for texture analysis [15]. Gabor elementary functions are Gaussians modulated by sinusoidal functions. The Gabor filters have adjustable orientation, radial frequency bandwidth, and center frequencies. Also they optimally achieve joint resolution in spatial and frequency domain. The 2-D Gabor filters have the functional form [16] as in Eq

\[ h(x,y) = g'(x,y) \exp(j(w_x x + w_y y)) \]


\[
g'(x, y) = \frac{1}{\lambda \sigma^2} g\left(\frac{x'}{\lambda \sigma}, \frac{y'}{\lambda \sigma}\right)
\]

\[
g(x, y) = \frac{1}{2\pi \sigma} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)
\]

The parameter \(\sigma\) is the spatial scaling, which controls the width of the filter, and \(\lambda\) defines the aspect ratio of the filter, which determines the directionality of the filters. It has spatial frequency

\[w = \sqrt{w_x^2 + w_y^2}\]

and direction

\[\theta = \tan^{-1}\left(\frac{w_y}{w_x}\right)\]

By varying the free parameters \(\sigma, \lambda, w\) and \(\theta\) filters of arbitrary orientation and bandwidths are obtained.

III. COMPARISON OF RESULTS

Gupta et al.[8] tested on iris images of CASIA database. Iris localization using hough transform performs better as compared to other localization techniques in case of occlusion due to eyelids and eyelashes. They achieved the overall accuracy of 95.4\% with FRR of 5\% and FAR 4\%. Amel Saeed Tuama[12] evaluated the performance of the biometric system using FAR and FRR. FAR is the rate at which an imposter print is incorrectly accepted as a genuine and FRR is rate at which a genuine print is incorrectly rejected as an imposter. When the number of subject is 60, the FAR and FRR are 2.43\% and 3.17\% respectively. They investigated that if more subjects are considered error rate increases. Naveen et al.[6] tested the project using Haar wavelet features on 60 images and obtained average of correct recognition of 95\%. The images were only classified against a database of 10 iris images by Greco et al.[15]. In contrast, the images that were misclassified were all images that included almost completely closed eyes. In addition, these images were typical rotated beyond the 10\(^\circ\) that is taken into account with the synthetic data. This system achieved an overall accuracy of 96.3\% percent. Li Ma et al.[17] test the algorithm in two modes: verifications and identifications. For each iris pattern, several patterns are randomly chosen for training and rest for the testing. An average overall recognition 95.68\% is achieved in testing of the samples with 3 training iris. An overall accuracy for different feature extraction methods in percent is shown in the Table-I.

IV. CONCLUSION

Every individual have unique physiological characteristics. Iris patterns may be used for reliable visual recognition. Available feature extraction methods for iris pattern are studied in this paper. This paper is an analysis of the result of the various feature extraction methods. The survey of the techniques provides a platform for the development of the novel techniques in this area as future work.

<table>
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<tr>
<th>Group</th>
<th>FAR/FRR</th>
<th>Overall Accuracy (%)</th>
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<tbody>
<tr>
<td>Singh et al.</td>
<td>95</td>
<td></td>
</tr>
<tr>
<td>Gupta et al.</td>
<td>4/5</td>
<td>95.4</td>
</tr>
<tr>
<td>Greco et al.</td>
<td>3/4</td>
<td>96.3</td>
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<tr>
<td>Amel Saeed Tuama</td>
<td>2.43/3.17</td>
<td>94.85</td>
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<tr>
<td>Li Ma</td>
<td></td>
<td>95.68</td>
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REFERENCES