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Multi-algorithmic Iris Authentication System

Hunny Mehrotra, Banshidhar Majhi, and Phalguni Gupta

***Abstract*—**The paper proposes a novel technique for iris recognition using texture and phase features. Texture features are extracted on the normalized iris strip using Haar Wavelet while phase features are obtained using LOG Gabor Wavelet. The matching scores generated from individual modules are combined using sum of score technique. The system is tested on database obtained from Bath University and Indian Institute of Technology Kanpur and is giving an accuracy of 95.62% and 97.66% respectively. The FAR and FRR of the combined system is also reduced comparatively.

***Keywords*—**Fusion, Haar Wavelet, Iris, LOG Gabor Wavelet, Phase, Texture.

I. Introduction

IRIS has become an interesting biometric modality with low false acceptances especially when there is a need to search a large database due to high pattern variability among different persons. Though iris is an internal organ of an eye, the patterns are externally visible and can be easily imaged from a distance. Iris patterns are apparently stable throughout the lifetime of an individual and hence can be used as a measure of personal authentication taking into consideration the aging factor that usually happens with face, ear etc.

The automated use of iris recognition as a means of authentication has been originally proposed by Flom and Safir [1]. Daugman has proposed an operational iris recognition system in 1994 [2]. Since then, iris biometric is evolved as a standard reference model for verification. From past research available, feature extraction techniques in iris can be roughly classified into four broad categories [3]

1. Texture based Method

The information lying between the pupillary and outer iris boundary is extracted and some texture analysis algorithm is applied to extract unique features [3][6][9]. This gives the amplitude information of the image.

2. Phase based Method

In this approach the phase angles are assigned to iris pattern by finding the sub-pixel image translation. Several known phase based approaches are given in [8].

3. Zero Crossing based Method

Zero-crossings of the wavelet transform at various resolution levels are calculated over concentric circles on the iris, and the resulting one-dimensional (1-D) signals are compared with model features using different dissimilarity functions [10].

4. Intensity Variation based Method

This technique takes into consideration the shape information of the iris by analyzing local intensity variations of an iris image [11].

There is abundant texture information in iris that is unique to each individual. By applying filters on the texture pattern gives the amplitude features. Phase information is used for recognizing irises because amplitude information is not very discriminating, and it depends upon extraneous factors such as imaging contrast, illumination, and camera gain [14]. Phase features are obtained regardless of the image contrast and illumination. The external lightening factor does not affect the functioning of the phase based systems. In the proposed work, an iris recognition system is developed that takes into consideration both amplitude and phase information. The domain of features increases in terms of texture and phase information for recognition. In this framework, iris biometric system operates on an input iris image taken from CCD or infrared cameras. All subsequent stages depend upon the quality of acquired input image. The input image is passed to preprocessing module as given in Section II. The transformed area underlying between inner pupil boundary and outer iris boundary is used for extraction of unique features. Here a novel combination of texture and phase based classifier is used for feature extraction. The texture information from normalized iris image is obtained using Haar wavelet decomposition [6] as given in Section III.A. and phase information is extracted using Laplacian of Gaussian (LOG) Gabor Wavelet [12] as given in Section III.B. The matching scores from the individual recognizers are combined using weighted sum of score technique and is given in Section IV. The experimental results for independent and combined classifier are discussed in Section V. Conclusions are given in the last section.

II. Iris Preprocessing

The image after acquisition is passed to preprocessing module because it defines the inner and outer boundaries of iris pattern used for feature analysis. Iris portion is delineated from the rest of the image using Circular Hough

H. Mehrotra is with the National Institute of Technology Rourkela, Rourkela-769008, India (phone: +91 9438490587; e-mail: hunny@nitrkl.ac.in).
B. Majhi is with the National Institute of Technology Rourkela, Rourkela-769008, India (e-mail: bmajhi@nitrkl.ac.in).
Phalguni Gupta is with the Indian Institute of Technology Kanpur, Kanpur-208016, India (e-mail: pg@iitk.ac.in).

Transformation [5]. The method can even detect circular objects affected by noise. Circular Hough Transform (CHT) is used to transform a set of true points in the binary image into parameter space. To detect the pupil boundary, first the edges are detected from an input image. Then at each edge point a circle is drawn of desired radius. At the coordinates which belong to perimeter of the drawn circle, the value in the accumulator is incremented every time. In this way every edge point is sweeped in the input image drawing circles with the desired radii and incrementing the values in the accumulator. For every edge point and every desired radius the accumulator contains numbers corresponding to the number of circles passing through the individual coordinates. Thus the highest number (selected in relation to the radius) corresponds to the center of the pupil circle in the image [4]. The Hough space representation of pupil localization is given in Fig. 1. Similarly, the outer iris boundary is detected for a larger range of radius as input.

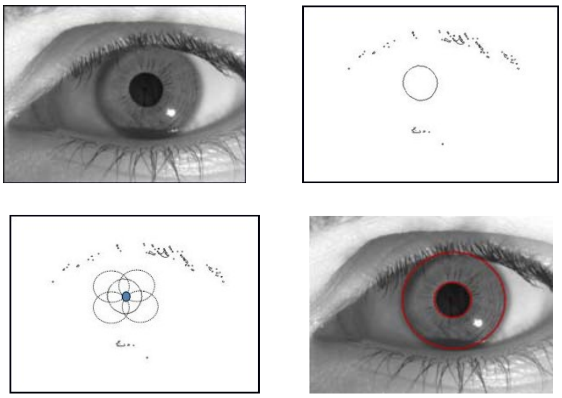

Fig. 1 (a) Original iris image (b) Edge detected (c) Hough space for localization (c) Localized iris image

Further, to achieve convenience for feature extraction and illumination invariance the localized portion is transformed into rectangular block known as strip using Daugman's rubber sheet model [8]. Here, the coordinate system is changed by unwrapping the iris and mapping all the points within the boundary of the iris into their polar equivalent. The size of the mapped image is fixed (60×360 pixels).

III. Feature Extraction

The features from the transformed iris strip are extracted using Haar Wavelet [6] and LOG Gabor Wavelet [12]. The two classifiers are chosen to have more number of features for matching comprising of texture pattern and phase information.

A. Haar Wavelet Decomposition

Haar Wavelet decomposition operates by calculating the sums and differences of intensity values [6]. The iris strip is taken as input to the process and at each level the algorithm finds four coefficients i.e., approximation, vertical, horizontal and diagonal. The process is again repeated for the generated approximation coefficients. This is again iterated for four levels and last level coefficients (horizontal, vertical, and diagonal) forms the feature set. The pictorial representation of feature extraction using Haar Wavelet is given in Fig. 2. The algorithm for Haar Wavelet decomposition is given in Algorithm 1.

Algorithm 1 Haar_Decompose(I: Strip, n: Decomposition Levels, C: Number of Columns, R: Number of Rows)

for d = 1 to n **do**
  for x = 1 to C **do**
    $H \leftarrow I_x + I_{x+1}$
    $H \leftarrow I_x - I_{x+1}$
    $x \leftarrow x+2$
  end for
  $H \leftarrow (1/\sqrt{2})H$
  for y= 1 to R **do**
    $H \leftarrow H_y + H_{y+1}$
    $H \leftarrow H_y - H_{y+1}$
    $y \leftarrow y+2$
  end for
  $H \leftarrow (1/\sqrt{2})H$
  $I \leftarrow H_{CA}$
  $R \leftarrow R/2$
  $C \leftarrow C/2$
end for

The horizontal, vertical, and diagonal coefficients from the last level are combined to form a feature vector. These feature elements are quantized against a threshold to generate iris code (IC_{Haar}) for enrollment and matching.

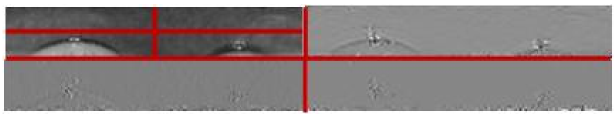

Fig. 2 Feature extraction using Haar Wavelet

B. LOG Gabor Wavelet

To obtain the phase information LOG Gabor wavelet is used for feature extraction. It has been observed [7] that the log filters (which use Gaussian transfer functions viewed on a logarithmic scale) can code natural images better than Gabor filters. Statistics of natural images indicate the presence of high-frequency components. Since the ordinary Gabor filters under-represent high frequency components, the log filters is a better choice.

An easier way of using the Gabor wavelet is by breaking up the 2-D normalized pattern into a number of 1-D signals, and

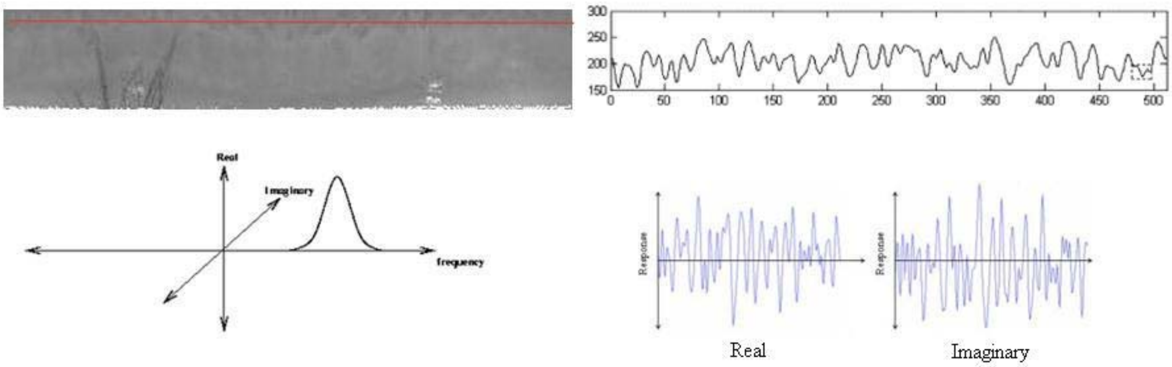

Fig. 3 LOG Gabor Wavelet on Iris Strip

then these signals are convolved with 1-D Gabor wavelets given by

$$G(f) = \exp\left(\frac{-\left(\log\left(\frac{f}{f_0}\right)\right)^2}{2\left(\log\left(\frac{\sigma}{f_0}\right)\right)^2} \right) \tag{1}$$

where f_0 represents the center frequency and σ represents bandwidth of the filter. The algorithm for LOG Gabor wavelet is given in Algorithm 2.

Algorithm 2 LOG_Gabor(I: Strip, R: Number of Rows of I)
for x = 1 to R **do**
  $H(x) \leftarrow G(f) \times I(x)$
end for

Using the output of LOG_Gabor, the iriscode (IC_{Gabor}) is formed by assigning two elements for each pixel of the output image H. Each element contains a value 1 or 0 depending on the sign of the real and imaginary part respectively. The process involved in feature extraction is given in Fig. 3.

Iris codes obtained through Haar Wavelet (IC_{Haar}) and Gabor Wavelet (IC_{Gabor}) are represented in the form of bit vectors.

IV. FUSION

In this section a new classifier using amplitude and phase information is proposed. Haar Wavelet and LOG Gabor wavelet perform better individually but the combined system takes the individual advantages of both the system. Phase based methods are invariant to illumination and contrast as compared to texture information that is largely dependent on illumination factors. However, Haar generates rich texture information from the iris strip.

The fusion module takes into consideration the scores generated from independent recognizers. The scores obtained after matching are combined using weighted sum of score technique. The iris codes of size $n \times m$ generated by Haar Wavelet during enrollment (IC^1_{Haar} and verification (IC^2_{Haar}) are compared to determine matching score using XOR operation as

$$MS_{Haar} = \frac{1}{n \times m} \sum_{i=1}^{n} \sum_{j=1}^{m} IC^1_{Haar}(i,j) \otimes IC^2_{Haar}(i,j) \tag{2}$$

Similarly the matching score for Gabor Wavelet (MS_{Gabor}) is calculated. The individual scores are passed to fusion module to generate a combined score. The combination is done as follows

$$MS_{final} = \alpha \times MS_{Haar} + \beta \times MS_{Gabor} \tag{3}$$

where MS_{final} is the score generated after fusion, α and β are the weights assigned to the classifiers based on performance such that $\alpha + \beta$ is equal to 1. The score (MS_{final}) is finally compared against threshold to find a match.

V. EXPERIMENTAL RESULTS

In this section the performance of the proposed iris recognition has been studied on the database available from BATH University [13] and Indian Institute of Technology Kanpur (IITK). The Bath university database comprises of 20 images of 100 subjects. However IITK database consists of 1800 iris images with three images per person (1800×3). The images at IITK are collected using CCD based iris camera.

For Bath dataset it is found that the individual recognizers Haar and Gabor Wavelet independently give an accuracy of 93.64% and 94.4% respectively. However the accuracy after fusion using scores increases to 95.62%. The accuracy versus threshold graph is given in Fig. 4.

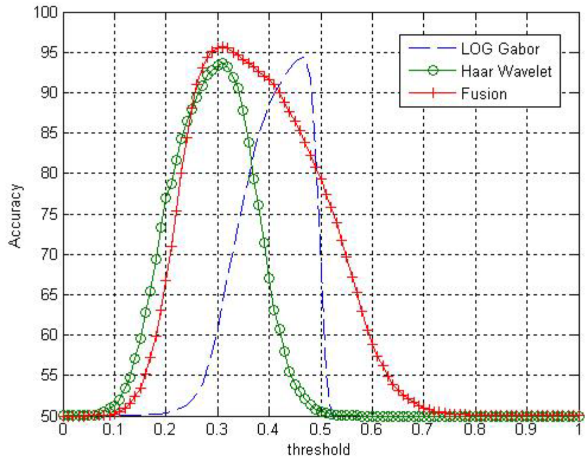

Fig. 4 Accuracy Graph for BATH database

On the other hand for IITK database the individual recognizers gives an accuracy of 95.89% and 96.31%. The fusion gives an enhanced accuracy of 97.66%. The accuracy graph is given in Fig. 5. This shows that combination leads to better performance due to presence of multiple matchers with varying characteristics.

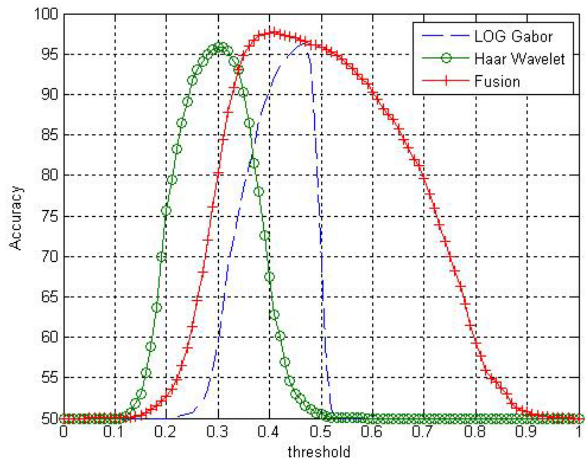

Fig. 5 Accuracy Graph for IITK database

From the experimental results it can be further inferred that False Acceptance Rate (FAR) of the combined matcher is reduced to an insignificant value as well as false rejection rate is also reduced comparatively. Table I shows FAR, FRR and Accuracy rates of individual as well as combined classifiers for BATH and IITK databases.

The Receiver Operating Characteristic (ROC) curve is a plot of False Acceptance Rate (FAR) against Genuine Acceptance Rate (GAR). ROC for the classifiers for BATH and IITK datasets is given in Fig. 6 and 7. From the curve it is evident that the combined system gives higher genuine acceptance at lower false rejections. The system is performing better in terms of reduced false rejection as shown in Table I. Thus the system can be deployed for high security applications with lower error probability.

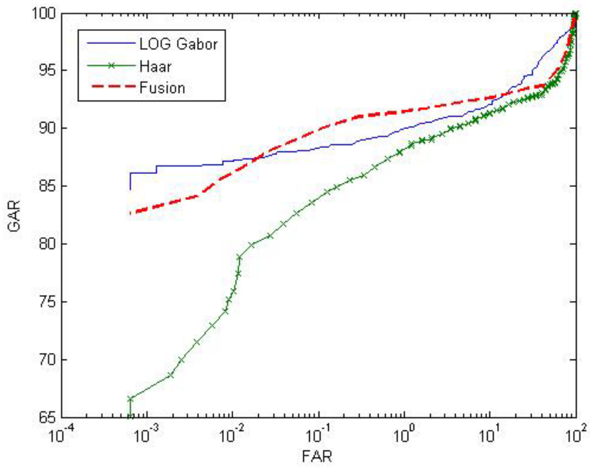

Fig. 6 ROC Curve for BATH

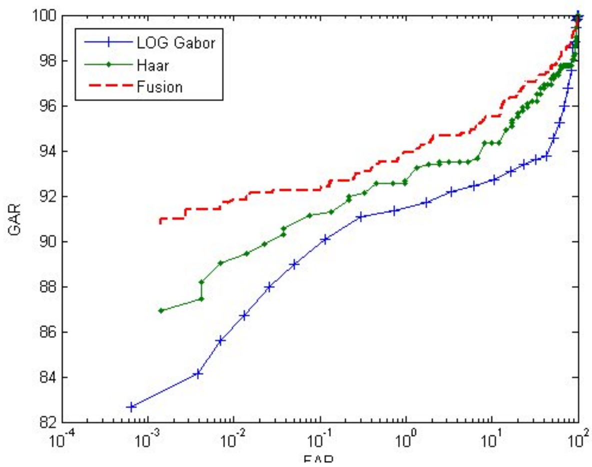

Fig. 7 ROC Curve for IITK database

VI. CONCLUSION

This paper presents an iris recognition system which combines amplitude and phase information for feature extraction. The two features acts as complimentary to each other during recognition. The texture information provides rich pattern details whereas phase features works independent of contrast and illumination. Thus the combined system performs better in terms of accuracy with reduced error rates. The scores are combined at matching score level and give an accuracy of more than 97%.

TABLE I
ERROR RATES AND ACCURACY

	BATH			IITK		
	FAR	**FRR**	**Accuracy**	**FAR**	**FRR**	**Accuracy**
Haar Wavelet	1.61	11.08	93.64	0.33	7.88	95.89
LOG Gabor Wavelet	1.63	9.55	94.40	1.30	6.05	96.31
Fusion	**0.36**	**8.38**	**95.62**	**0.16**	**4.50**	**97.66**

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