Gabor Filter for Accurate IRIS Segmentation Analysis

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Abstract - Iris recognition has been used with very satisfactory result. the parameter selection is the difficult premise of the feature extraction by 2D-Gabor filter. This paper, based on a detailed analysis of the variation between the frequency, scale, orientation and the decidability index proposes a suitable selection method for the extraction of the iris texture features with 2D-Gabor filter and then applies it to achieve the entire iris recognition. experimental results gives the methods of designing filter has a strong capability of recognition.

***Keywords*: Computer Application, Iris Recognition, 2D-Gabor Filter, Feature Extraction.**

I. INTRODUCTION

Different from other biometrics, iris recognition, with its distinctive advantage in physical aspect has been widely used in airports, banks, prisons and other occasions with high security requirements. Therefore it has been studying by researchers from all over the world and many different approaches of iris recognition have been designed [1-8]. One of the most representatives of the algorithm is a two-dimensional Gabor filter proposed by Daugman, that is, iris texture feature extraction. Then it is followed by a lot of literature which aimed at further study and improvement of the method [9-11], but they mainly focused on the system frame and matching algorithms and with little mention of the filter parameters selection the difficult premise of feature extraction. the partial iris image a simple and efficient 2D-Gabor filter is designed with which the analysis of the role of different parameters of the filter in their performance is presented, and thus a new set of filter parameter selection method of extracting iris-based energy orientation features.

II. IRIS IMAGE PRE-PROCESSING

Iris image preprocessing includes iris localization, normalization, and image enhancement. Iris localization is to identify the effective area outside the pupil and within the sclera. For the sake of subsequent image comparison, normalization is the process of unfolding the collected iris image of different sizes under the same size of the rectangular area in the polar coordinate. Iris image enhancement is intended to overcome the low contrast in image acquisition, uneven illumination, and the big divergence in two gray images of the same, which may exert negative impact on the iris recognition result. This normalized image size is 512×64, which intercepts the eyelids, eyelashes, etc. As 128×64 ROI are rarely relatively interfered with, they can be effective texture regions for subsequent feature comparisons through horizontal displacement of the intra-class image [12]. The purpose of the horizontal comparison is to eliminate the error caused by rotation of the iris, and to improve similarity of characteristics within the same category, as it is shown in

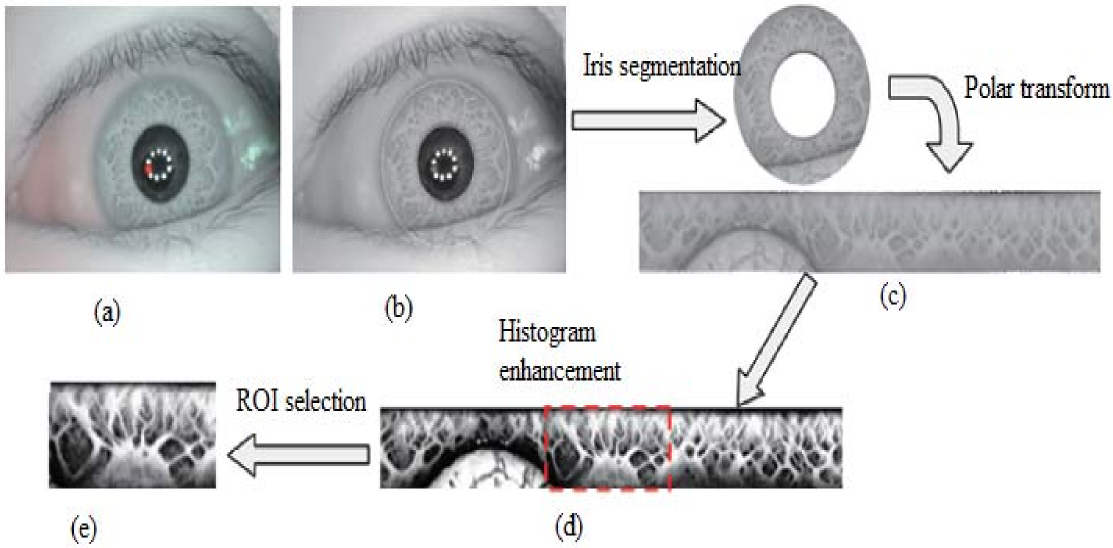


Fig. 2.1: Iris image pre-processing; (a) Original eye image; (b) Iris localization; (c) Iris normalization; (d) Normalized image enhancement; (e) ROI

III. GABOR FILTER DESIGNING

The feature extraction based Gabor filter have been widely used in iris and fingerprint recognition. A multichannel Gabor wavelet is a set of filter banks with different orientations and different scales, which is used to extract texture features of various densities and piece them together for a formation of an iris image texture feature coding.

3.1 2D-Gabor Filter

Gabor filters are able to provide optimum conjoint representation of a signal in space and special frequency. A Gabor filter is made up by modulating a sine / cosine wave with a Gaussian filter. This is able to offer the optimum conjoint localization in both space and frequency since a sine wave is perfectly denoted in frequency but not denoted in space. Modulation of the sine with a Gaussian provides localisation in space though with loss of localisation in frequency. Decomposition of a signal is modified using a quadrature pair of Gabor filters with a real part specified by a cosine modulated by a Gaussian, and an imaginary part specified by a sine modulated by a Gaussian. The real and imaginary filters are also known as the even symmetric and odd symmetric components respectively.

The centre frequency of the filter is specified by the frequency of the sine/cosine wave and the bandwidth of the filter is modulated by the width of the Gaussian.

Daugman makes uses of a 2D version of Gabor filters [1] in order to encode iris pattern data. A 2D Gabor filter over the an image domain (x, y) is represented as

$$G(x,y) = e^{-\pi[(x-x_o)^2]/\alpha^2 + [(y-y_o)^2/\beta^2]} e^{-2\pi i[u_o(x-x_o)cos\theta] + [v_o(y-y_o)]sin\theta]} \quad (1)$$

where (x_o, y_o) specify position in the image (α, β) specify the effective width and length, and (u_o, v_o) specify modulation which has special frequency

$$\omega_0 = \sqrt{u_0^2 + v_0^2} \qquad (2)$$

Daugman demodulates the output of the Gabor filters in order to compress the data. This data is compress by quantising the phase information into four types levels which is divided into possible quadrant in the complex plane.

These four levels are represented using two bits of data so each pixel in the normalised iris pattern corresponds to two bits of data in the iris system. This template are very storage and gives comparison of irises. The Daugman system makes use of polar coordinates for normalization therefore in polar form the filters are given as

$$H(r,\theta) = e^{-i\omega(\theta-\theta_0)}\, e^{-(r-r_0)^2/\alpha^2}\, e^{-i(\theta-\theta_0)^2/\beta^2}] \qquad (3)$$

where *(α, β)* are the same as in Equation 3.1 and *(r_0, θ_0)* specify the centre frequency of the filter.

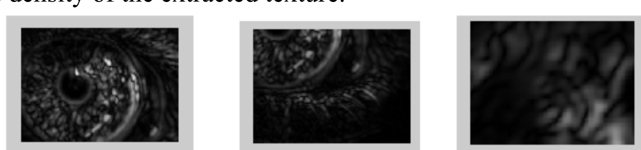
The demodulation and phase Quantisation process can be represented as

$$H_{(Re,Im)} = sgn_{(Re,Im)} \int_\rho \int_\phi I(\rho,\phi)\, e^{-i\omega(\theta_0-\phi)}\, e^{-(r_0-\rho)^2/\alpha^2}\, e^{-(\theta_0-\phi)^2/\beta^2}]\rho\, d\rho\, d\phi \qquad (4)$$

where H{Re, Im} can be regarded as a complex valued bit whose real and imaginary components are dependent on the sign of the 2D integral and I(φ, ρ) is the raw iris image in a dimensionless polar coordinate system. For a detailed study of 2D Gabor wavelets see [6].

3.2 Frequency Parameters Selection

From the signal, the response is strongest when the frequency of the extracted features and that of the filter are the same. Therefore, it demonstrates that the 2D-Gabor filter is frequency selective, extraction of the specified degree of sparse texture can be achieved by the adjustment of the frequency ω. It is shown in Fig. 3.1 that an amplitude image is taken by the filter when the ROI of the angle parameter is $\theta = 0$, ω takes 1.07, 0.45, 0.31 the smaller the value ω, the less density of the extracted texture.



(a) $w = 1.07$ (b) $w = 0.45$ (c) $w = 0.31$

Fig. 3.1: Magnitude image

the original ROI image, wherein (a) and (b) are the same kind of iris images, (c) being other classes. Images are different feature ones under different frequency in which different gray represent different orientation feature when the filter angle is 0, $\pi/4$, $\pi/2$, $3\pi/4$. It is safe to conclude that the larger ω, the more delicate of the extraction of iris feature, which means reducing the inter-class similarity may also lowering the intra-class one and vice verse. Whether the frequency is relatively high or not, d' will be reduced all the same. Therefore, the discovery of a balanced point ω_0 within conflicting parameters makes d' the biggest and thus the distinguish ability is the strongest. The index of decidability d' is calculated as follows:

$$d' = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{(\sigma_1^2 + \sigma_2^2)}{2}}} \qquad (5)$$

where μ_1 and σ_1 are the means and standard deviations of dissimilarities of intra-class, while μ_2 and σ_2 are that of inter-class. As can be seen from Fig. 3.2, the distribution of d' and ω is a single peak curve, especially, when the ω_0 = 0.50025, d' reaches 5.67087. Therefore, the higher area [$\omega_0 - 0.05$, $\omega_0 + 0.05$] of ω_0 near d' is determined as filter frequency range. In this paper, filter banks is based on sampling points such as ω=0.50 as the center frequency and ω_1=0.45, ω_2=0.55 as two boundary points.

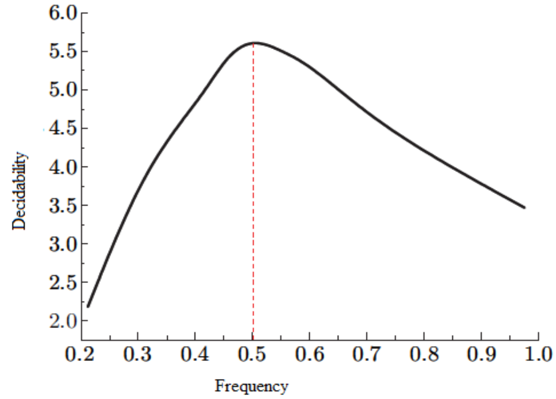


Fig. 3.2 Relation between frequency and decidability

3.3 *Scale Parameters Selection*

The scale of filter defining the Gabor in the spatial domain, scale and frequency are inverse proportionally. As shown in below, a similar multi-scale set of wavelet on basis of different frequency serves to extract different dense texture with different scale filters.

$$\tau = Round[\frac{(6\times\sigma)}{\omega} + 1] \tag{6}$$

where τ is filter scale, σ is standard deviations of Gaussian, and the latter determines the bandwidth of filter and the size of Gaussian together with octave and scale, and ω is the filter center frequency. The frequency follows its correspondent scale value, so is the decidability of the maximum index. According to the previous Eq. (6) calculation, the maximum index scales are 52, 53, 62 respectively, and the d' are 5.458995, 5.696898, 5.895669 respectively.

3.4 ***Angle Parameters Selection***

The angle determines the orientation of the texture feature extracted by the filter. As they are in equal probability distribution in each orientation and the filter is in the specific symmetry in the angular orientation, we can just aliquot angles within the range of 0s π. Shown in Fig. 3.3 there is a single curve maxima between the number of angles and d', i.e. when the number of angles takes eight, angle increments $\pi/8$, d' reaches the maximum 6.117087.

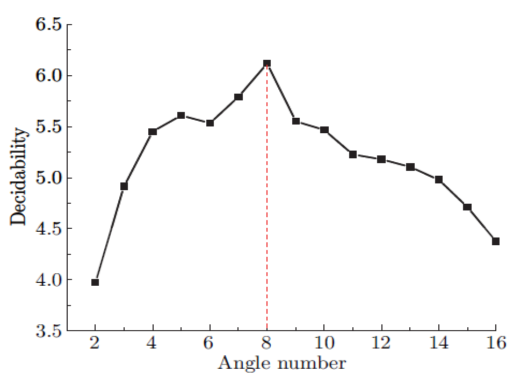


Fig. 3.3 Relation between angle number and decidability

IV. IRIS FEATURE EXTRACTION

In this stage, texture analysis methods are used to extract the significant features from the normalized IRIS image. The extracted features will be encoded to generate a biometric template. The filtered ROI according to Eq. (1) results in the real and imaginary parts as the response of the Gabor filter. The magnitude of the Gabor filtered image is calculated using Eq. (7) - (9), and the features of the matrix are realized by comparing the magnitude of different orientations. Specific operations are shown in Eq. (10):

$$Re = \frac{w^2}{\sigma^2} e^{-\frac{w^2(x^2+y^2)}{2\sigma^2}}\left[\cos(wx\cos\theta + wy\sin\theta) - e^{\frac{-\sigma^2}{2}}\right] \quad (7)$$

$$Im = \frac{w^2}{\sigma^2} e^{-\frac{w^2(x^2+y^2)}{2\sigma^2}}\left[\sin(wx\cos\theta + wy\sin\theta)\right] \quad (8)$$

$$Mag^2[k] = Re^2[k] + Im^2[k] \quad (9)$$

$$FM = sgn\{\max(Mag[k])\} \quad (10)$$

where σ is the Gaussian standard deviation, θ is the angle of the filter, ω is the central frequency. Fig 4.1 Explain the DC component frees the transformation of 2D-Gabor wavelet from the absolute value of gray and the image not that sensitive to illumination changes. *Re* and *Im* are the real and imaginary of the filter.

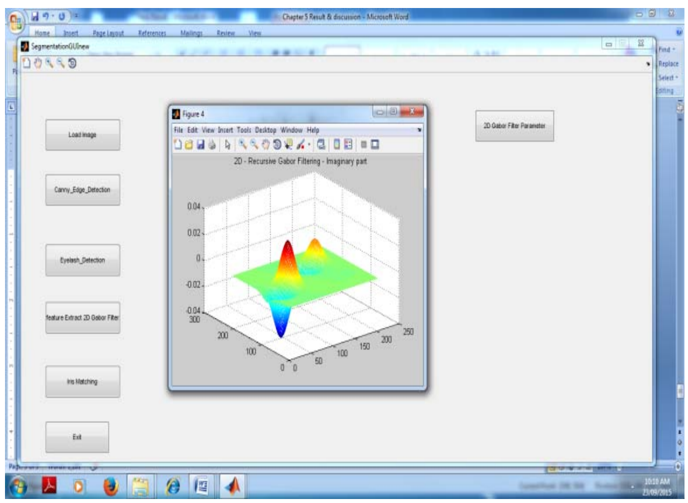


Fig 4.1 Real and Imaginary of the filter

V. MATCHING

The similarity (index *SIM*) between samples serves as iris matching basis. *SIM* is a fractional measure of similarity, 1 would represent a perfect match. Calculation results in the appropriate degree of similarity as a decision threshold. If the similarity between two featured encoding is larger than the threshold value, that is the same iris; otherwise heterogeneous ones. Similarity calculation formula is as follows

$$SIM = \frac{1}{T}\sum_{i=1}^{T} FM_a \otimes FM_b \quad (11)$$

where *FMa* and *FMb* represent two feature matrix, *T* is the number of elements of feature matrix, ⊗ represents *XNOR*. Fig 5.1 show the Iris Template of matching.

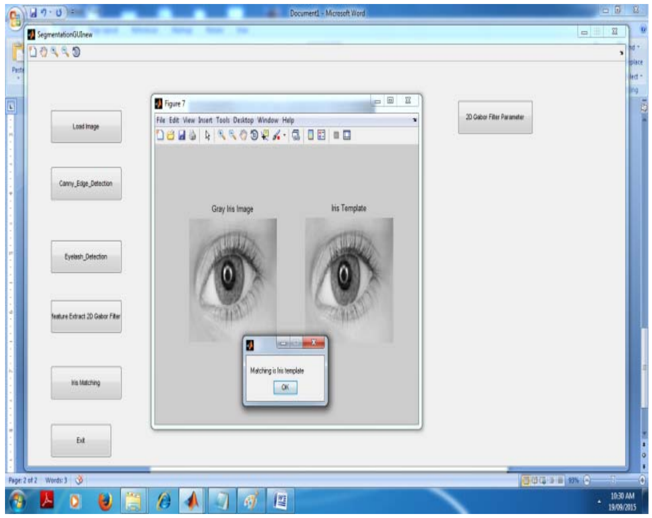


Fig 5.1 Matching of Iris Template

VI. ACKNOWLEDGEMENT

I would like to extend my sincere thanks to all of them. I am highly indebted to Prof. Meenakshi R Patel for their guidance and constant supervision as well as for providing necessary information regarding the paper. I would like to express my gratitude towards my parents & professors of my college for their kind cooperation and incouragement which help me in completion of this paper.

VII. CONCLUSIONS

This paper analyzes the variation of the 2D-Gabor filter frequency, scale and angle number, and decidability indicators. It also discusses how these parameters may influence the filter performance. Based on the analysis a 2D-Gabor filter design suitable for local iris texture parameters is made. It is shown in experimental results that such design is capable of iris classification on a small scale sample set. However, in the future, application of the design to large-scale iris image database should be carried out in order to further validate its versatility and robustness.

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