Iris Recognition System Using Fractal Dimensions of Haar Patterns

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Abstract

Classification of iris templates based on their texture patterns is one of the most effective methods in iris recognition systems. This paper proposes a novel algorithm for automatic iris classification based on fractal dimensions of Haar wavelet transforms is presented. Fractal dimensions obtained from multiple scale features are used to characterize the textures completely. Haar wavelet is applied in order to extract the multiple scale features at different resolutions from the iris image. Fractal dimensions are estimated from these patterns and a classifier is used to recognize the given image from a data base. Performance comparison was made among different classifiers.

Keywords: *Haar wavelet, fractal dimension, box counting, Euclidean classifier, K-NN classifier*

1. Introduction

Two phases are involved during authentication process using a biometric system, enrollment and authentication. During enrollment features sets are extracted from iris textures and saved in database. During authentication the features are extracted from query iris template and classified against the database.

Current iris recognition systems perform exhaustive matching with high computational complexity as large databases are to be considered. Thus this new iris recognition system will play a vital role in reducing both the search time and computational complexity by classifying into different categories.

Iris texture exhibits a rich source of visual information-about the nature and three dimensional shapes of physical objects. Textures are complex visual patterns composed of entities, or sub patterns that have characteristic brightness, color, slope, size. Thus texture can be regarded as a similarity grouping in an image (Rosenfeld 1982). The local sub-pattern properties give rise to the perceived lightness, uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation of the texture as a whole (Levine 1985).

Van Gool [5] and Reed and Buf [6] present a detailed survey of the various texture methods used in the image analysis studies. The recognition ability of classifiers depends on the quality of features used as well as the amount of training data available to them. Image features are mostly extracted on shape and texture of segmented objects. Karu [7] defines a methodology for automatically identifying textured regions within an image so that feature extraction algorithms are used only where texture can be quantified.

Julesz (1975) found that for a large class of textures "no texture pair can be discriminated if they agree in their second order statistics". Therefore the major statistical method used in texture analysis is the one based on the definition of the joint probability distributions of pairs of pixels. Weska [9] compared the Fourier spectrum, second order gray levels statistics, co-occurrence statistics and gray level run length statistics and found that the co-occurrence were the best.

Mandlebort [25], was the person to introduce the fractals to estimate the roughness of a surface. Fractal-based metrics capture texture properties, such as the ranges and frequency of self-similar surface peaks, which are not possible by using traditional measures [16]. Fractal dimension extracts roughness information from images considering all available scales at once. Single scale features may not be sufficient to characterize the textures, thus multiple scale features are considered necessary for a more complete textural representation [24]. Wavelets are employed for the computation of single and multiple scale roughness features due to their ability to extract information at different resolutions.

Recent developments involve decomposition of the image in terms of wavelets which provide information about the image contained in smaller regions also. Gabor filters [10] and Haar wavelets [11] can be used for this purpose. A Wavelet transformation converts data from the spatial into the frequency domain and then stores each component with a corresponding matching resolution scale [11]. Wavelets are used to represent different levels of details. The Haar wavelet is one of the simplest wavelet transforms. Haar wavelet transform can transform huge data sets to considerably smaller representations.

In this paper, we propose a novel iris recognition system based on fractal dimensions of Haar patterns. The rest of the paper is organized as follows. Section 2 introduces the proposed method. Section 3 describes implementation details. Section 4 comes out with experimental results and their discussion. Section 5 concludes the whole paper.

2. Proposed method

The process of iris recognition typically involves the following stages: (a) iris segmentation, where the iris is localized and isolated from the noise due to sclera, pupil, eyelids and eyelashes; (b) normalization, where iris is mapped from polar domain to rectangular domain; (c) decomposition, where the rectangular entity is projected onto 5 level Haar wavelet to decompose into deterministic patterns (d) reduction of feature space , the coefficients that represent the core of the iris pattern are retained and that reveal redundant information are eliminated; (e) box counting method is used to find the fractal dimensions of each pattern and feature set is developed with the help of these dimensions (f) Classification, both probabilistic and non probabilistic classifiers such as Bayes, Euclidean and K-Nearest Neighbor and weighted Euclidean are used in the experiment.

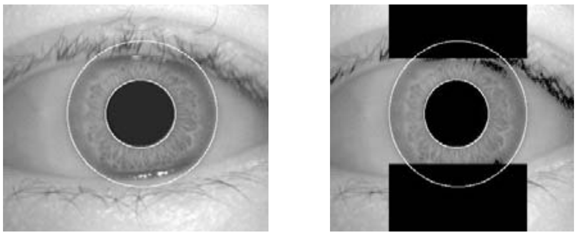
3. Implementation details

3.1 Iris Localization and Normalization

Iris localization mainly involves two basic operations, one is to detect eye lids and the other is boundary detection. The first step involves extraction of circular shaped iris rim by removing the noisy regions. Eyelids and eyelashes occlude upper and lower parts of the iris. Thus these regions must be segmented. The second step is to detect the inner and outer boundaries of iris. One is at the transition region of iris and sclera and the other is at the iris and pupil.

Canny edge detection is performed both in vertical direction and horizontal directions as suggested by Wildes et al [12]. The iris images in CASIA database has iris radius 80 to 150 and pupil radius from 30 to 75 pixels, which were found manually and were given to the Hough transform. If we apply Hough transform first for iris/sclera boundary and then to iris/pupil boundary then the results are accurate. The output of this step results in storing the radius and x, y parameters of inner and outer circles.

Canny edge detection is used to create edges in horizontal direction and then Hough transform is implemented on it. If the maximum Hough space is less than the threshold it represents non occlusion of eyelids. For isolating eyelashes it is easier by using thresholding, since they are darker when compared with other elements in eye.



(a) Iris after boundaries detected (b) Iris image after noise removal

Figure 1. Iris Localization

The eye images collected are of gray scale and their contrast is enhanced using histogram equalization.

Daugman suggested normal Cartesian to polar transformation that maps each pixel in the iris area into a pair of polar coordinates(r, θ), where r and θ are on the intervals of [0 1] and [0 2π] .

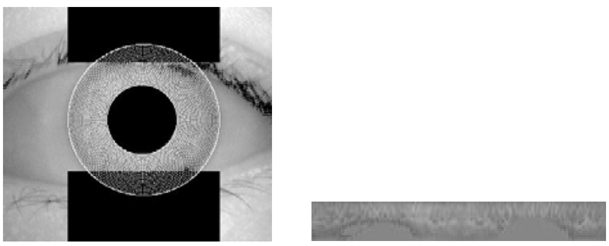
This unwrapping can be formulated as

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \qquad (1)$$

Such that

$$x(r, \theta) \rightarrow (1-r)\, x_p(\theta) + r\, x(\theta)$$
$$y(r, \theta) \rightarrow (1-r)\, y_p(\theta) + r\, y(\theta) \qquad (2)$$

where $I(x, y)$, (x, y), (r, θ), (x_p, y_p), (x_i, y_i) represent the iris region, Cartesian coordinates, polar coordinates, coordinates of the pupil and iris boundaries along θ direction respectively. Thus this representation often called as rubber sheet model. Rotational inconsistencies are not considered in this representation.



(a) Polar form of Flower iris image (b) Normalized form of Flower iris

Figure 2. Iris Normalization

3.2 Decomposition

Haar transform is real and orthogonal. Haar Transform is a very fast transform. The basis vectors of the Haar matrix are sequence ordered. The original signal is split into a low and a high frequency part and then filters will do the splitting without duplicating information and they may be called orthogonal. The magnitude response of the filter is exactly zero outside the frequency range covered by the transform. If this property is satisfied, the transform is energy invariant. In the Haar transform, it has the perfect reconstruction property since the input signal is transformed and inversely transformed by using a set of weighted basis functions and the reproduced sample values are identical to those of the input signal. Also it is ortho normal since; no information redundancy is present in the sampled signal. The Haar wavelet transform has a number of advantages like it is conceptually simple, fast, memory efficient and exactly reversible when compared with other wavelets.

A 5-level Haar wavelet is decomposed into 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). Among these only cD4h, cD_4^v, cD_4^d, cD_5^h, cD_5^v, cD_5^d represent the core of the iris patterns. cD_1^h, cD_2^h, cD_3^h, cD_4^h are almost same with redundant information, hence they can be removed. Thus we can represent an image applied to Haar wavelet as the combination of six matrices:

- cD_4^h and cD_5^h
- cD_4^v and cD_5^v
- cD_4^d and cD_5^d

3.3 Box counting method

The word fractal refers to the degree of self similarity at different scales. Fractal dimension can be used to discriminate between textures of similar sets. Box counting method is one of the wide variety of methods for estimating the fractal dimension [27], which can be automatically applied to patterns with or without self similarity.

An image of size R x R pixels, is partitioned into grids measuring s x s, where $1 \leq s \leq R/2$. Then $r = s/R$. If the minimum and maximum gray scale levels in the $(i, j)^{th}$ grid fall into, the k^{th} and l^{th} boxes, respectively, the contributions of n_r in the $(i, j)^{th}$ grid is defined as

$$n_r\ (i, j) = l - k + 1 \ \text{ and } \ N_r = \sum_{i,j} n_r\,(i, j); \qquad (3)$$

N_r is computed from different values of r and the fractal dimension FD can be estimated as the slope of the line joining these points (log (1/r), log N_r). the linear regression equation to estimate the fractal dimension is

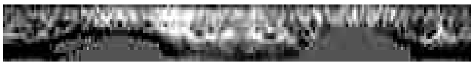
$$\mathrm{Log}(N_r) = \log(k) + FD \log(1/r), \qquad (4)$$

Where k is a constant and FD denotes dimension of the fractal set.

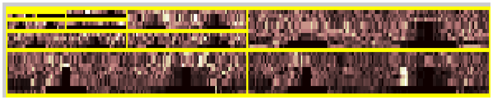
This FD can be also called as entropy dimension, Kolmogorov entropy, capacity dimension, metric dimension and Minkowski dimension. It provides description of how much of the surface it fills.

Fractal dimensions for all the above six matrices representing haar patterns FD_4^h, FD_5^h, FD_4^v, FD_5^v FD_4^d, FD_5^d are computed using the above method and combined to form a single feature vector:

$$\begin{pmatrix} FD_4^h & FD_5^h \\ FD_4^v & FD_5^v \\ FD_4^d & FD_5^d \end{pmatrix}$$



a) Sample image before decomposition



b) After decomposition

Figure 3. Haar wavelet decomposition

3.4 Classification

A training data set is used to train a classifier and another test data set is used to test the classifier. Both the probabilistic and non probabilistic distance measures such as Bayes, Euclidean, K-Nearest Neighbor [4] are used.

If the features are assumed to have Guassian density function, Bayes classifier is optimal. Bayes classifier is given by

$$d_j(x) = \ln P(w_j) - \frac{1}{2} \ln |C_j| - \frac{1}{2}\{(x - m_j)^T C_j^{-1}(x-m_j)\} \quad (5)$$

Euclidean classifier depends only on the mean positions of the texture classes. Euclidean classifier is given by

$$d_j(x) = \sum_{k=1}^{n}(x_k - m_{j,k})^2 \quad (6)$$

In K-NN, the unknown sample data is classified by assigning it the label most frequently represented among the k nearest samples. K-Nearest Neighbor classifier is given by

$$d_j(x)= P(w_j|x) \text{ if K –nearest neighbors of x are labeled } w_j \quad (7)$$

4. Experimental results

Experimental evaluation of recognition system is carried on the iris images collected from CASIA Iris image Database [V3.0] and MMU Iris Database [MMU04a]. CASIA Iris Image Data base contributes a total number of 756 iris image which were taken in two different time frames and 249 subjects. Each of the iris images is 8-bit gray scale with resolution 320 X 280. MMU data base contributes a total number of 450 iris images which were captured by LG Iris Access®2200. Entire experiment is carried using MATLAB 7.4 and the process involves two phases. One is training phase and the other is classification phase.

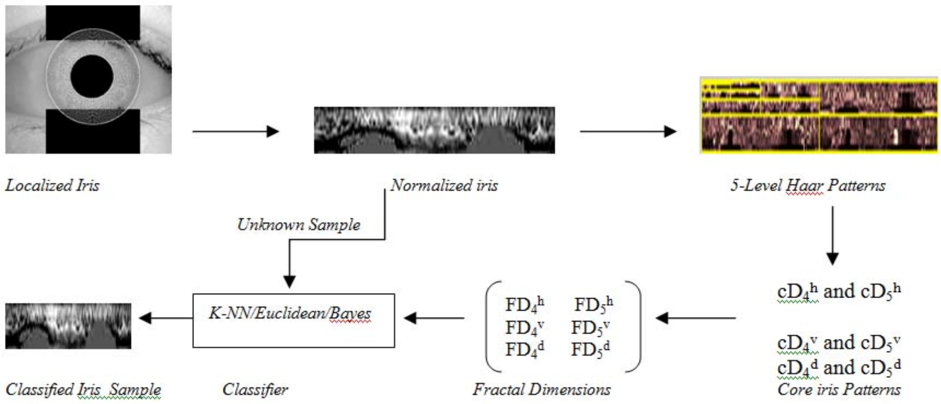


Figure 4. Algorithm for iris classification

4.1 Training Phase

1. Two hundred and forty samples (linear iris templates with 10 pixel radial resolution and 240 pixel angular resolution) are extracted using localization and normalization techniques from the above data base.
2. Each sample is applied to 5 level Haar wavelet to extract the deterministic patterns.
3. Redundancy is removed by eliminating all the coefficients except cD_4^h, cD_4^v, cD_4^d, cD_5^h, cD_5^v, $cD_5^{d.}$
4. For each above pattern fractal dimension FD is estimated using box counting method.
5. A 2D vector is formed by using these fractal dimensions.
6. Steps 2-5 are repeated for all the two hundred and forty samples.

4.2 Classification Phase

1. Feature vector of an iris sample that is to be classified is computed as in steps 2-5 of training phase.
2. A classifier is used to identify the unknown sample.
3. Steps 1-2 are repeated with three different classifiers such as Bayes, Euclidean and K-NN.
4. Steps 1-3 are repeated for all two hundred and forty samples.

4.3 Discussion

Our results showed good classification rate, as we have considered multi scale features from core of the iris patterns. Calculation of fractal dimensions will be quite unlike if we consider the haar patterns of all levels as some of them (cD_1, cD_2 and cD_3) have low resolution. Also to reduce the time complexity we have considered patterns at level 4 and 5 only. Percentage of correct classification (PCC) of four samples is tabulated in Table 1. One hundred and eighty training samples and the same number of testing samples are used, almost all 100% PCC is obtained with all training samples. Individual results for the classification 180 samples are summarized in Table 2. 100% correct classification is achieved for 160 samples and PCC for the remaining is above 90%. It is opined that the % PCC will increase if the number of samples are increased and finally it reaches the saturation point.

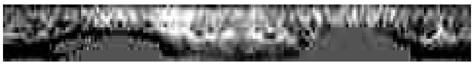


Figure 5. Sample 1

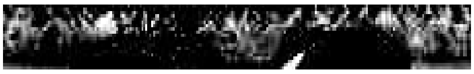


Figure 6. Sample 2

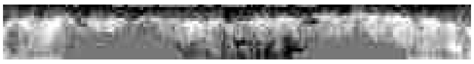


Figure 7. Sample 3

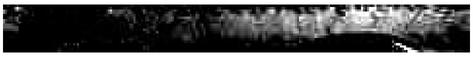


Figure 8. Sample 4

Table 1.Comparision of different classifiers

Iris sample	*% correct classification (PCC)*		
	Bayes	*Euclidean*	*K-NN*
Sample 1	*90*	*100*	*100*
Sample 2	*89*	*100*	*100*
Sample 3	*84*	*100*	*100*
Sample 4	*81*	*97*	*94*

Table 2. Overall PCC for all samples

%PCC	Number of samples classified
100	160
95-99	12
90-94	8

Table 3. PCC with and without Haar patterns of sample -1

Classifier	% correct classification (PCC)	
	Using FD from original image	Using FD from Haar Patterns
K-NN	94	100
Euclidean	98	100
Bayes	84	90

5. Conclusion

An efficient algorithm for iris recognition based on fractal dimensions of Haar patterns has been developed which reduces overheads against exhaustive search and high computational complexities of traditional recognition systems. As non redundant Haar patterns are only considered for developing feature space, it is more reliable and reduces time complexity in classification. The experiments and results prove the robustness and versatility of algorithm.

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