# A Novel Method Using Contourlet to Extract Features for Iris Recognition System

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**Abstract.** In different areas of Biometrics, recognition by iris images in nowadays has been taken into consideration by researchers as one of the common methods of identification like passwords, credit cards or keys. Iris recognition a novel biometric technology has great advantages such as variability, stability and security. Although the area of the iris is small it has enormous pattern variability which makes it unique for every one and hence leads to high reliability. In this paper we propose a new feature extraction method for iris recognition based on contourlet transform. Contourlet transform captures the intrinsic geometrical structures of iris image. It decomposes the iris image into a set of directional sub-bands with texture details captured in different orientations at various scales so for reducing the feature vector dimensions we use the method for extract only significant bit and information from normalized iris images. In this method we ignore fragile bits. At last, the feature vector is created by using Co-occurrence matrix properties. For analyzing the desired performance of our proposed method, we use the CASIA dataset, which is comprised of 108 classes with 7 images in each class and each class represented a person. And finally we use SVM and KNN classifier for approximating the amount of people identification in our proposed system. Experimental results show that the proposed increase the classification accuracy and also the iris feature vector length is much smaller versus the other methods.

**Keywords:** Biometric–Iris Recognition, Contourlet Transform, Co-occurrence Matrix, Support Vector Machine (SVM).

## 1 Introduction

There has been a rapid increase in the need of accurate and reliable personal identification infrastructure in recent years, and biometrics has become an important technology for the security. Iris recognition has been considered as one of the most reliable biometrics technologies in recent years [1, 2]. The human iris is the most important biometric feature candidate, which can be used for differentiating the individuals. For systems based on high quality imaging, a human iris has an extraordinary amount of unique details as illustrated in Fig.1. Features extracted from the human iris can be used to identify individuals, even among genetically identical twins [3]. Iris-based recognition system can be noninvasive to the users since the iris is an internal organ as well as externally visible, which is of great importance for the real-time

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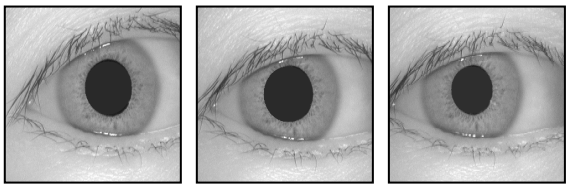

**Fig. 1.** Samples of iris images from CASIA [7]

applications [4]. Based on the technology developed by Daugman [3, 5, 6], iris scans have been used in several international airports for the rapid processing of passengers through the immigration which have pre registered their iris images.

### 1.1 Related Works

The usage of iris patterns for the personal identification began in the late 19th century; however, the major investigations on iris recognition were started in the last decade. In [9], the iris signals were projected into a bank of basis vectors derived by the independent component analysis, and the resulting projection coefficients were quantized as Features. A prototype was proposed in [10] to develop a 1D representation of the gray-level profiles of the iris. In [11], biometrics based on the concealment of the random kernels and the iris images to synthesize a minimum average correlation energy filter for iris authentication were formulated. In [5, 6, 12], the Multiscale Gabor filters were used to demodulate the texture phase structure information of the iris. In [13], an iris segmentation method was proposed based on the crossed chord theorem and the collarette area. An interesting solution to defeat the fake iris attack based on the Purkinje image was depicted in [16]. An iris image was decomposed in [17] into four levels by using the 2D Haar wavelet transform, the fourth-level high-frequency information was quantized to form an 87-bit code, and a modified competitive learning neural network (LVQ) was adopted for classification.

Fourth-level high-frequency information was quantized to form an 87-bit code, and a modified competitive learning neural network (LVQ) was adopted for classification. In [18], a modification to the Hough transform was made to improve the iris segmentation, and an eyelid detection technique was used, where each eyelid was modeled as two straight lines. A matching method was implemented in [19], and its performance was evaluated on a large dataset. In [20], a personal identification method based on the iris texture analysis was described. The remainder of this paper is organized as follows: Section 2 deals with proposed method. Section 3 deals with Feature Extraction method discussion. Section 4 deals with feature subset selection and vector creation techniques, Section 5 shows our experimental results and finally Section 6 concludes this paper.

## 2 Proposed Method: The Main Steps

Fig. 2 illustrates the main steps of our proposed Approach. First the image preprocessing step performs the localization of the pupil, detects the iris boundary, and isolates the collarette region, which is regarded as one of the most important areas of the iris

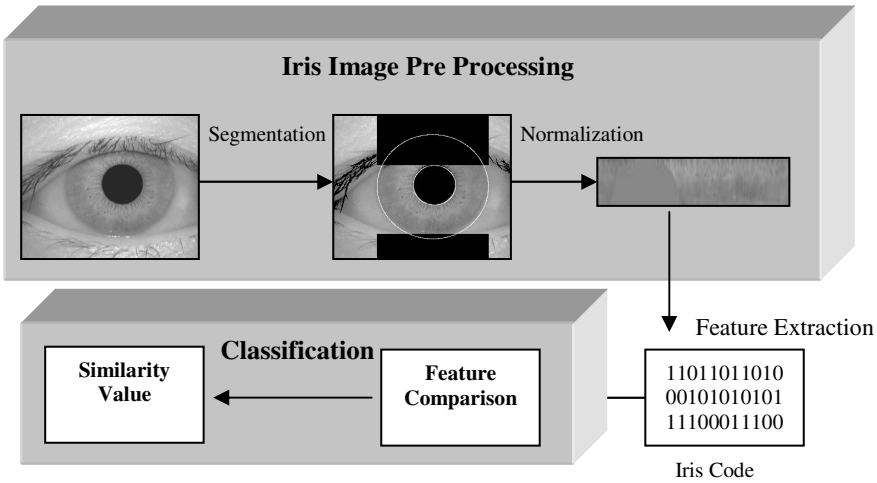


**Fig. 2.** Flow diagram of the proposed iris recognition scheme

complex pattern. The collarette region is less sensitive to the pupil dilation and usually unaffected by the eyelids and the eyelashes [8]. We also detect the eyelids and the eyelashes, which are the main sources of the possible occlusion. In order to achieve the invariance to the translation and the scale, the isolated annular collarette area is transformed to a rectangular block of fixed dimension.

The discriminating features are extracted from the transformed image and the extracted features are used to train the classifiers. The optimal features subset is selected using several methods to increase the matching accuracy based on the recognition performance of the classifiers.

### 2.1 Iris Image Preprocessing

First, we outline our approach, and then we describe further details in the following subsections. The iris is surrounded by the various non relevant regions such as the pupil, the sclera, the eyelids, and also noise caused by the eyelashes, the eyebrows, the reflections, and the surrounding skin [9].We need to remove this noise from the iris image to improve the iris recognition accuracy.

#### 2.1.1 Iris / Pupil Localization

The iris is an annular portion of the eye situated between the pupil (inner boundary) and the sclera (outer boundary). Both the inner boundary and the outer boundary of a typical iris can be taken as approximate circles. However, the two circles are usually not concentric [20].

#### 2.1.2 Eyelids, Eyelashes, and Noise Detection

- Eyelids are isolated by first fitting a line to the upper and lower eyelids using the linear Hough transform. A second horizontal line is then drawn, which intersects with the first line at the iris edge that is closest to the pupil [20].

- Separable eyelashes are detected using 1D Gabor filters, since a low output value is produced by the convolution of a separable eyelash with the Gaussian smoothing function. Thus, if a resultant point is smaller than a threshold, it is noted that this point belongs to an eyelash.
- Multiple eyelashes are detected using the variance of intensity, and if the values in a small window are lower than a threshold, the centre of the window is considered as a point in an eyelash as shown in Fig .3.

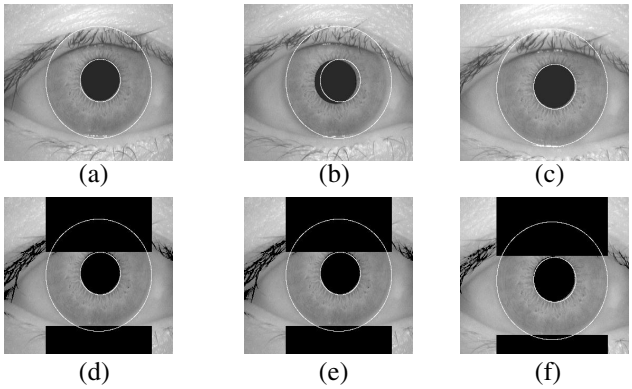


**Fig. 3.** CASIA iris images (a), (b), and (c) with the detected Collarette area and the corresponding images (d), (e), and (f) after Detection of noise, eyelids, and eyelashes

#### 2.1.3 Iris Normalization

We use the rubber sheet model [12] for the normalization of the isolated collarette area. The center value of the pupil is considered as the reference point, and the radial vectors are passed through the collarette region. We select a number of data points along each radial line that is defined as the radial resolution, and the number of radial lines going around the collarette region is considered as the angular resolution. A constant number of points are chosen along each radial line in order to take a constant number of radial data points, irrespective of how narrow or wide the radius is at a particular angle. We build the normalized pattern by backtracking to find the Cartesian coordinates of data points from the radial and angular positions in the normalized pattern [3, 5, and 6]. The normalization approach produces a 2D array with horizontal dimensions of angular resolution, and vertical dimensions of radial resolution form the circular-shaped collarette area (See Fig.4I). In order to prevent non-iris region data from corrupting the normalized representation, the data points, which occur along the pupil border or the iris border, are discarded. Fig.4II (a) (b) shows the normalized images after the isolation of the collarette area.

## 3 Feature Extraction and Encoding

Only the significant features of the iris must be encoded so that comparisons between templates can be made. Gabor filter and wavelet are the well-known techniques in

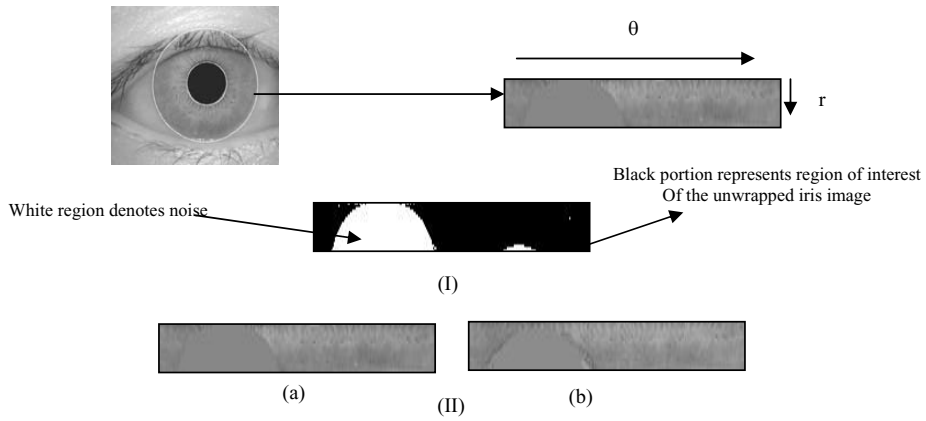


**Fig. 4.** (I) shows the normalization procedure on CASIA dataset; (II) (a), (b) Show the normalized images of the isolated collarette regions

texture analysis [5, 19, 20, 21]. In wavelet family, Haar wavelet [22] was applied by Jafer Ali to iris image and they extracted an 87-length binary feature vector. The major drawback of wavelets in two-dimensions is their limited ability in capturing Directional information. The contourlet transform is a new extension of the wavelet transform in two dimensions using Multi scale and directional filter banks.

The feature representation should have information enough to classify various irises and be less sensitive to noises. Also in the most appropriate feature extraction we attempt to extract only significant information, more over reducing feature vector dimensions, the processing lessened and enough information is supplied to introduce iris feature vectors classification.

### 3.1 Contourlet Transform

Contourlet transform (CT) allows for different and flexible number of directions at each scale. CT is constructed by combining two distinct decomposition stages [33], a multistage decomposition followed by directional decomposition. The grouping of wavelet coefficients suggests that one can obtain a sparse image expansion by applying a multi-scale transform followed by a local directional transform. It gathers the nearby basis functions at the same scale into linear structures. In essence, a wavelet-like transform is used for edge (points) detection, and then a local directional transform for contour segments detection. A double filter bank structure is used in CT in which the Laplacian pyramid (LP) [23] is used to capture the point discontinuities, and a directional filter bank (DFB) [24] to link point discontinuities into linear structures. The combination of this double filter bank is named pyramidal directional filter bank (PDFB) as shown in Fig.5.Benefits of Contourlet Transform in the Iris Feature Extraction To capture smooth contours in images, the representation should contain basis functions with variety of shapes, in particular with different aspect ratios. A major challenge in capturing geometry and directionality in images comes from the discrete nature of the data; the input is typically sampled images defined on rectangular grids.

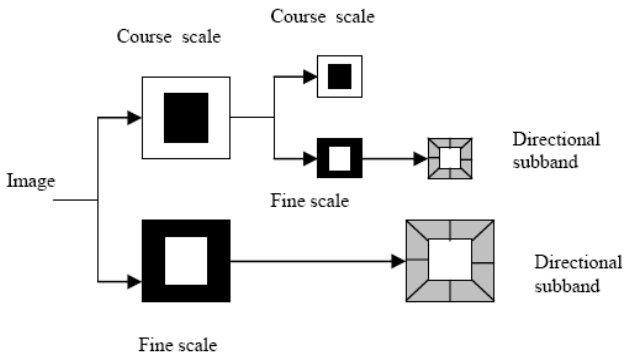


**Fig. 5.** Two Level Contourlet Decomposition [33]

Because of pixelization, the smooth contours on sampled images are not obvious. For these reasons, unlike other transforms that were initially developed in the continuous domain and then discretized for sampled data, the new approach starts with a discrete-domain construction and then investigate its convergence to an expansion in the continuous-domain. This construction results in a flexible multi-resolution, local, and directional image expansion using contour segments. Directionality and anisotropy are the important characteristics of contourlet transform. Directionality indicates that having basis function in many directions, only three direction in wavelet. The anisotropy property means the basis functions appear at various aspect ratios where as wavelets are separable functions and thus their aspect ratio is one. Due to this properties CT can efficiently handle 2D singularities, edges in an image**.** This property is utilized in this paper for extracting directional features for various pyramidal and directional filters.

### 3.2 The Best Bit in an Iris Code

Biometric systems apply filters to iris images to extract information about iris texture. Daugman's approach maps the filter output to a binary iris code. The fractional

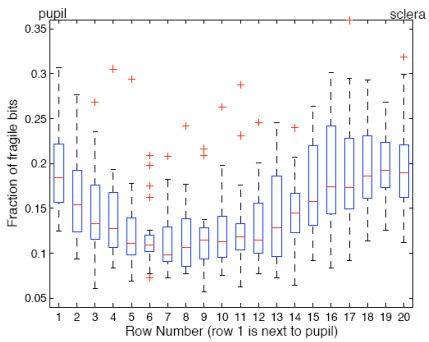


**Fig. 6.** Percent of Fragile Bit in Iris Pattern [25]

Hamming distance between two iris codes is computed and decisions about the identity of a person are based on the computed distance. The fractional Hamming distance weights all bits in an iris code equally. However, not all the bits in an iris code are equally useful. For a given iris image, a bit in its corresponding iris code is defined as "fragile" if there is any substantial probability of it ending up a 0 for some images of the iris and a 1 for other images of the same iris. According to [25] the percentages of fragile bits in each row of the iris code, Rows in the middle of the iris code (rows 5 through 12) are the most consistent (See Fig. 6.)

## 4 Feature Vector Creation in Proposed Method

According to the method mentioned in section 3.2, we concluded the middle band of iris normalized images have more important information and less affected by fragile bits, so for introducing iris feature vector based on contourlet transform the rows between 5 and 12 in iris normalize image are decomposed into eight directional subband outputs using the DFB at three different scales and extract their coefficients. In our method we use using the Grey Level Co-occurrence Matrix (GLCM).The technique uses the GLCM (Grey Level Co-occurrence Matrix) of an image and it provides a simple approach to capture the spatial relationship between two points in a texture pattern. It is calculated from the normalized iris image using pixels as primary information. The GLCM is a square matrix of size G * G, where G is the number of gray levels in the image. Each element in the GLCM is an estimate of the joint probability of a pair of pixel intensities in predetermined relative positions in the image. The $(i, j)^{th}$ element of the matrix is generated by finding the probability that if the pixel location (x , y) has gray level $I_i$ then the pixel location (x+dx , y+dy) has a gray level intensity $I_j$. The dx and dy are defined by considering various scales and orientations. Various textural features have been defined based on the work done by Haralick [26]. These features are derived by weighting each of the co-occurrence matrix values and then summing these weighted values to form the feature value. The specific features considered in this research are defined as follows:

1) Energy $= \sum_i \sum_j p(i,j)^2$

2) Contrast $= \sum_{n=0}^{N_g-1} n^2 \left[ \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i,j) \| i-j \| = n \right]$

3) Correlation $= \dfrac{\sum_i \sum_j (ij) P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$

4) Homogeneity$= \sum_i \sum_j \dfrac{1}{1+(i-j)^2} P(i,j)$

5) Autocorrelation $= \sum_i \sum_j (ij) P(i,j)$

6) Dissimilarity = $\sum_i \sum_j |i-j|.P(i,j)$

7) Inertia = $\sum_i \sum_j (i-j)^2 P(i,j)$

Here $\mu_x, \mu_y, \sigma_x, \sigma_y$ are mean and standard deviation along x and y axis.

## 5 Experimental Results

For creating iris feature vector we carried out the following steps:

1) Iris normalized image (Rows in the middle of the iris code (rows 5 through 12)) is decomposed up to level two.(for each image, at level one, 2 and at level two, 4 sub band are created).
2) The sub bands of each level are put together, therefore at level one a matrix with 4*120 elements, and at level two a matrix with 16*120 elements is created. We named these matrixes: Matrix1 and Matrix 2.
3) By putting together Matrix1 and Matrix 2, a new matrix named Matrix3 with 20*120 elements is created. The co-occurrence of these three matrixes with offset one pixel and angles 0, 45, 90 degree is created and name this matrix: CO1, CO2 and CO3.in this case for each image 3 co-occurrence matrixes with 8*8 dimensions are created.
4) According to the Haralick‘s [26] theory the co-occurrence matrix has 14 properties, of which in iris biometric system we used 7 properties which are used for 3 matrixes , so the feature vector is as follow:

F=[ En1,Cont1,cor1,hom1,Acor1,dis1,ine1, En2,Cont2,cor2, hom2,Acor2,dis2,ine2 En3,Cont3,cor3,hom3,Acor3,dis3,ine3] In other word the feature vector in our method has only 21 elements. Also for improving results, for each sub bands and scale we create a feature vector by using GLCM.in other words for each eight sub bands in level 3 of Contourlet transform we computed GLCM properties, separately and then by combining these properties the feature vector is created. In this case the feature vector has 56 elements. In Table 1 you can see the result of implementing our proposed method:

**Table 1.** Result of Implementing Proposed Method

| The Number Of Classes | The Correct of Percentage Classification (%) | | |
|---|---|---|---|
| | KNN Classifier | SVM Classifier(Kernel 1) | SVM Classifier(Kernel 2) |
| 20 | 96.6 | 100 | 100 |
| 40 | 88.3 | 94.3 | 96.3 |
| 60 | 90.8 | 91.6 | 95.6 |
| 80 | 89.3 | 90.1 | 95.8 |
| 100(GLCM) | 88.5 | 90.07 | 94.2 |
| 100(GLCM (Combining Sub bands) | 87.5 | 91.3 | 96.3 |

In Table 2 we compared our proposed method with some other well known methods from 2 view points: feature vector length and the correct of percentage classification:

**Table 2.** Comparison Between Our Proposed Method and Some well- known Method

| Method | The Correct Of Percentage Classification (%) | The Feature Vector Length(Bit) |
|---|---|---|
| Dugan[3] | 100 | 2048 |
| Lim[17] | 90.4 | 87 |
| Ma[20] | 959 | 1600 |
| Jafar Ali[22] | 92.8 | 87 |
| | **Our Methods** | |
| (GLCM) | 94.2 | 21 |
| GLCM (Combining Sub bands) | 96.3 | 56 |

## 6 Conclusions

In this paper we proposed an effective algorithm for iris feature extraction using contourlet transform Co-occurrence Matrix have been presented. The GLCM proved to be a good technique as it provides reasonable accuracy and is invariant to iris rotation. For Segmentation and normalization we use Daugman methods .Feature extraction in our proposed method includes: sub bands proper composition from Contuorlet pyramid and co-occurrence calculations and finally selecting a set of Haralick‘s properties that form the Maximum distance between inter classes and Minimum distance between intra classes. Our proposed method can classify iris feature vector properly. The rate of expected classification for the fairly large number of experimental date in this paper verifies this claim. In the other words our method provides a less feature vector length with an insignificant reduction of the percentage of correct classification.

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