

A NOVEL METHOD FOR IRIS FEATURE EXTRACTION BASED ON CONTOURLET TRANSFORM AND CO- OCCURRENCE MATRIX

Amir Azizi

Islamic Azad University, Mashhad Branch

Hamid Reza Pourreza

Ferdowsi University of Mashhad, Department of computer engineering

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

The purpose of ‘Iris Recognition’, a biometrical based technology for personal identification and verification, is to recognize a person from his/her iris prints. In fact, iris patterns are characterized by high level of stability and distinctiveness. Each individual has a unique iris (see Figure.1); the difference even exists between identical twins and between the left and right eye of the same person.

Various iris recognition methods have been proposed for automatic personal identification and verification. In Figure.2 you can see the typical stages of Iris Recognition system. Daugman first presented a prototype system (Daugman, J., 1993, 2004) for iris recognition based on multi-scale Gabor wavelets. Wildes presented another iris recognition system (Wildes, R. P, et al., 1996) in which the iris pattern was decomposed into multi-resolution pyramid layers using wavelet transform. Both systems of Daugman and Wildes employed carefully designed image acquisition devices to get equal high quality iris images. Zhenan presented a shift-invariant method (Zhenan Sun et al., 2005) which decomposed the iris pattern into multiple bands using a two-dimensional Gabor filter. Boles & B.Boashash (Boles W.W and Boashash B, 1998) decomposed one-dimensional intensity signals computed on circles in the iris and use zero-crossings of the decomposed signals for the feature representation.

The number of zero-crossings can differ among iris image samples of an identical iris due to noises. This methods was improved (De Martin-Roche, D., et al., 2001) (Sanchez-Avila, C. et al.,2002)(Zhenan Sun

et al.,2005) in which it was assumed that if two samples were acquired from an identical iris the distances between corresponding pairs of zero-crossing in one sample and another were less than given threshold value. However, the spurious zero-crossing points could degrade the performance.

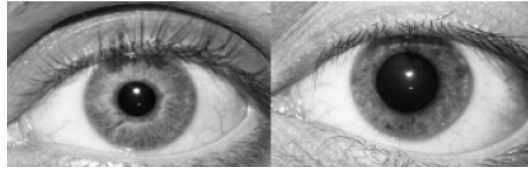


Figure 1. Distinctiveness of human iris

A well-established fact that the usual two-dimensional tensor product wavelet bases are not optimal for representing images consisting of different regions of smoothly varying grey-values separated by smooth boundaries. This issue is addressed by the directional transforms such as contourlets, which have the property of preserving edges. The contourlet transform is an efficient directional multi-resolution image representation which differs from the wavelet transform. The contourlet transform uses non-separable filter banks developed in the discrete form; thus it is a true 2D transform, and overcomes the difficulty in exploring the geometry in digital images due to the discrete nature of the image data.

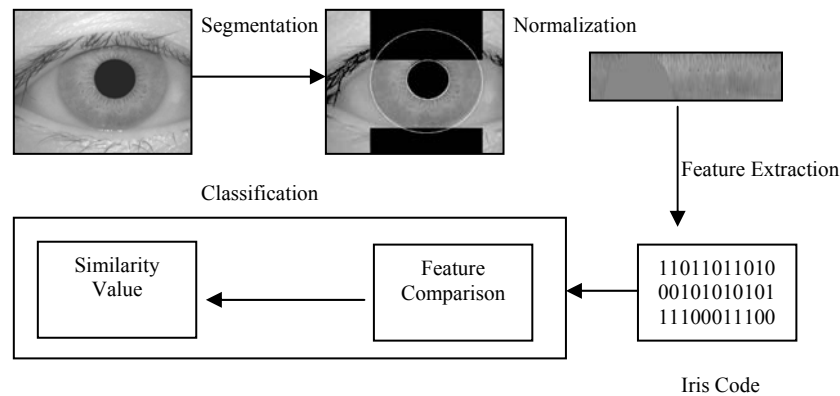


Figure 2. Typical stages of iris recognition

An iris image, as shown in Figure 3(a), contains not only the region of interest (iris) but also some ‘un useful’ parts (e.g. eyelid, pupil etc.). In addition, a change in the camera-to-eye distance may result in the possible variation in the size of the same iris. Furthermore, the brightness is not uniformly distributed because of non-uniform illumination. Before extracting features from the original image, the image needs to be preprocessed to localize iris, normalize iris, and reduce the influence of the factors mentioned above. Such preprocessing is described in the following subsections.

The remainder of this paper is organized as follows: Section 2 deals with Iris Recognition System overview. Section 3 deals with Experimental results and discussion. Section 4 concludes this paper.

2. IRIS RECOGNITION SYSTEM OVERVIEW AND PROPOSED METHOD

In this section we first overview the iris recognition system and then describe the proposed method for iris feature extraction.

2.1 Iris Localization (Segmentation)

Both the inner boundary and the outer boundary of a typical iris can approximately be taken as circles. However, the two circles are usually not co-centric. The iris is localized in two steps: (1) approximate region of iris in an image can be found by projecting iris image in horizontal and vertical direction. (2) The exact parameters of these two circles are obtained by using edge detection and Hough transform in a certain region determined in the first step. An example of iris localization is shown in Figure 3(b).

2.2 Iris Normalization

Irises from different people may be captured in different size, and even for the iris from the same person, the size may change because of the variation of the illumination and other factors. Such elastic deformations in iris texture affect the results of iris matching. For the purpose of achieving more accurate recognition results, it is necessary to compensate for these deformations. Here, we anti-clockwise unwrap the iris ring to a rectangular block of texture of a fixed size (20x240) by piecewise linear mapping. The distortion of the iris caused by pupil dilation can thus be reduced. The result after iris normalization is shown in Figure 3c.

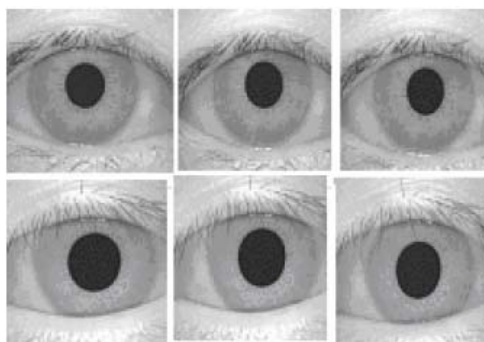


Figure3 (a). Iris image sample (CASIA version 1)

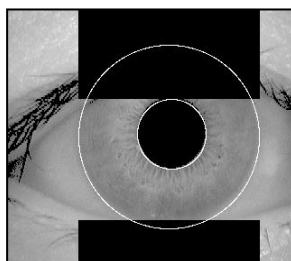


Figure 3(b). Localized (Segmented) iris by Daugman method

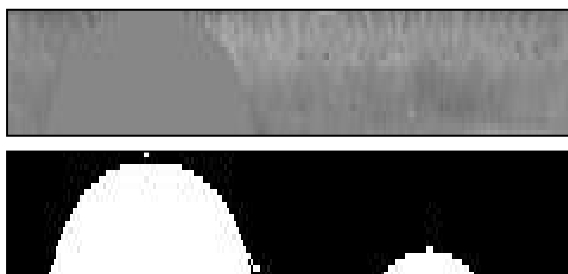


Figure 3(c). Normalized Iris

2.3 Feature Extraction in the Proposed Method

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 texture analysis (Ma, L., et al., 2002, 2003) (Daugman, J., 1993, 2004) (Zhu, Y. et al., 2000) In wavelet family, Haar wavelet (Jafar M. H. Ali, Aboul Ella Hussanien, 2003) 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 enough information to classify various irises and be less sensitive to noises. Also in the most appropriate feature extraction we attempt to extract only significant information, moreover reducing feature vector dimensions. Therefore the processing lessened and enough information is supplied to introduce iris feature vectors classification.

2.3.1 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 (Do M. N., and Vetterli, M., 2004), a multi-scale 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) (Burt P. J and Adelson E. H., 1983) is used to capture the point discontinuities, and a directional filter bank (DFB) (Bamberger R.H and Smith M. J. T., 1992) to link point discontinuities into linear structures. The combination of this double filter bank is named pyramidal directional filter bank (PDFB) as shown in Figure.4.

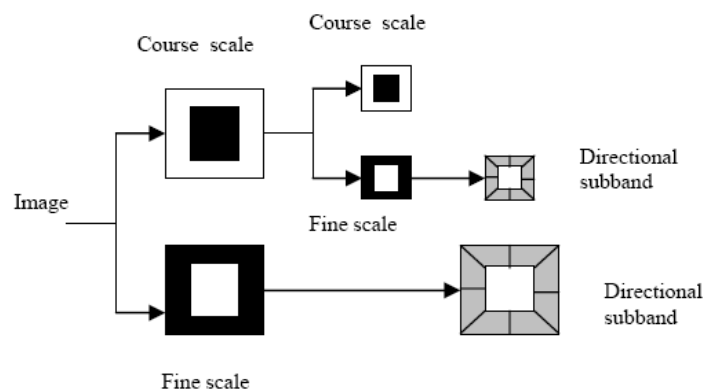


Figure 4. Two Level Contourlet Decomposition [12]

2.3.2 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. 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.

2.3.3 The Best Bits in an Iris Code

Iris 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 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 (Karen P. Hollingsworth, Kevin W. Bowyer, 2008) the percentage 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 Figure. 5).

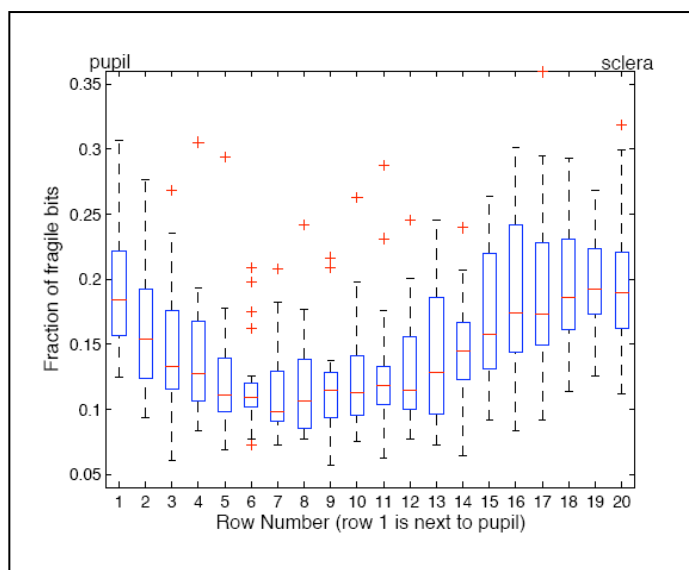


Figure 5. Percent of Fragile Bit in Iris Pattern

2.4 Feature Vector in Proposed Method

According to the method mentioned in section 2.3.1.3, 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 sub-band outputs using the DFB at three different scales and extract their coefficients. In our method we use 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 [Haralick, R.M, et al., 1973]. 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:

$$\begin{aligned}
 1) \text{ Energy} &= \sum_i \sum_j p(i, j)^2 \\
 2) \text{ Contrast} &= \sum_{n=0}^{N_g-1} n^2 \left[\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} P(i, j) \|i - j\| = n \right] \\
 3) \text{ Correlation} &= \frac{\sum_i \sum_j (ij)P(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \\
 4) \text{ Homogeneity} &= \sum_i \sum_j \frac{1}{1 + (i - j)^2} P(i, j) \\
 5) \text{ Autocorrelation} &= \sum_i \sum_j (ij)P(i, j) \\
 6) \text{ Dissimilarity} &= \sum_i \sum_j |i - j| \cdot P(i, j) \\
 7) \text{ Inertia} &= \sum_i \sum_j (i - j)^2 P(i, j)
 \end{aligned}$$

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

3. EXPERIMENTAL RESULTS

To evaluate the performance of this proposed system we use ‘‘CASIA’’(CASIA, 2003) iris image database (version 1) created by National Laboratory of pattern recognition, Institute of Automation, Chinese Academy of Science that consists of 108 subjects with 7 sample each. Images of ‘‘CASIA’’ iris image database are mainly from Asians. For each iris class, images are captured in two different sessions. The interval between two sessions is one month. There is no overlap between the training and test samples.

In our experiments, two-level contourlet decomposition is adopted. The above experiments are performed in Matlab 7.0. The normalized iris image obtained from the localized iris image is segmented by Daugman method. The contourlet transform of the image is shown in Figure 6. We have used the filters designed by A. Cohen, I. Daubechies, and J.-C. Feauveau. For the quincunx filter banks in the DFB stage.

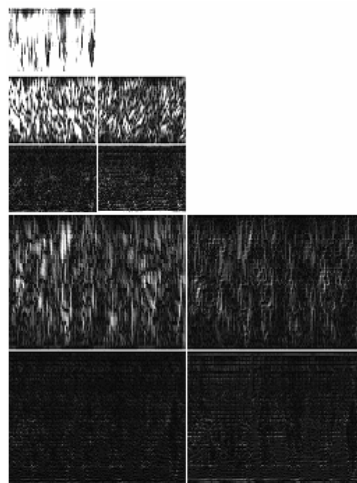


Figure 6. Contourlet Coefficient of an iris images.

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)) are 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 (Haralick, R.M, et al., 1973) 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 words the feature vector in our method has only 21 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	88.5	90.07	94.2

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)
Daugman(1993)	100	2048
Wildes(1996)	94.18	>2048
Ma(2002)	95.02	1600
Ma(2003)	92.22	1320
Jafar Ali(2003)	92.16	87
Our Method	94.2	21

4. CONCLUSION

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 data in this paper verifies this claim. In other words our method provides a less feature vector length with an insignificant reduction of the percentage of correct classification.

REFERENCES

- Bamberger, R.H., and Smith M. J. T, 1992. *A filter bank for the directional decomposition of images: Theory and design*, IEEE Trans. Signal Proc., vol. 40, no. 4, pp. 882–893.
- Boles, W.W., and Boashash B, 1998. *A Human Identification Technique Using Images of the Iris and Wavelet Transform*, IEEE Trans. Signal Processing, Vol.46, No.4, 1998, pp.1185-1188.
- Burt P. J., and Adelson E. H., 1983. *The Laplacian pyramid as a compact image code*, IEEE Trans. Commun., vol. 31, no. 4, pp. 532–540.
- Daugman, J., 1993. *High confidence visual recognition of persons by a test of statistical independence*, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 15, No. 11, pp: 1148-1160.
- Daugman, J., 2004. *How Iris Recognition works*. IEEE Transactions on Circuits and systems for video Technology, Vol.14, No.1, pp: 21-30.
- Do M. N., and Vetterli, M, 2004. *The contourlet transform: an Efficient directional multi-resolution image representation*, IEEE Transactions on Image Processing, vol. 14, issue 12, pp. 2091-2106.
- Haralick, R.M, et al., 1973. *Textural features for image classification*, IEEE Transactions on Systems, Man, and Cybernetics, vol.3, no.6, and pp.610-621.
- Karen P. Hollingsworth, Kevin W. Bowyer, 2008. *The Best Bits in an Iris Code*, IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI).
- Ma, L, et al. 2003. *Personal identification based on iris texture analysis*, IEEE Trans. Patt. Analy. & Mach. Intel vol. 25, No. 12, pp. 1519-1533.
- Sanchez-Avila, C. et al., 2002. *Iris-based biometric recognition using dyadic wavelet transform*, IEEE Aerospace and Electronics Systems Magazine, Volume: 17 Issue 10, pp. 3-6.
- Wildes, R. P, et al., 1996, *A machine-vision system for iris recognition*, Machine Vision and Applications, Springer-Vela.
- Zhenan Sun et al., 2005. *Improving Iris Recognition Accuracy via Cascaded Classifier*, IEEE Transactions on systems, Man and Cybernetics-part C: Applications reviews, Vol.35, No.3.
- CASIA, 2003. *Chinese Academy of Sciences – Institute of Automation, Database of 756 Grayscale Eye Images*. <http://www.sinobiometrics.com> Version 1.0.
- De Martin-Roche, D., et al., 2001. *Iris recognition for biometric identification using dyadic wavelet transform zero crossing*, IEEE Int. Carnahan Conference on Security Technology, pp. 272-277.
- Jafar M. H. Ali, Aboul Ella Hussanien, 2003. *An Iris Recognition System to Enhance E-security Environment Based on Wavelet Theory*, AMO - Advanced Modeling and Optimization, Volume 5, Number 2.
- Ma, L, et al., 2002. *Iris Recognition Based on Multichannel Gabor Filtering*, Proc. Fifth Asian Conf. Computer Vision, vol. I, pp. 279-283.
- Zhu, Y. et al., 2000. *Biometric Personal Identification Based on Iris Patterns*, Proc. Int'l Conf. Pattern Recognition, vol. II, pp. 805-808.