A NOVEL TECHNIQUE FOR IRIS RECOGNITION SYSTEM

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Abstract: 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.

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. 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, 1996, et al) 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. 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

Figure 1 illustrates the main steps of our proposed Approach. First the image preprocessing step performs the localization of the pupil, detects the iris

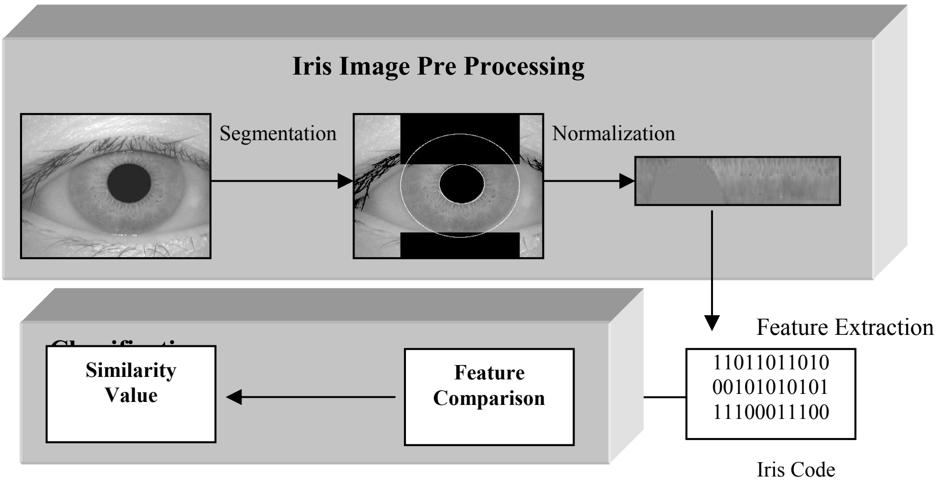

Figure 1: Flow diagram of the proposed iris recognition scheme.

boundary, and isolates the collarette region, which is regarded as one of the most important areas of the iris complex pattern. The collarette region is less sensitive to the pupil dilation and usually unaffected by the eyelids and the eyelashes 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 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 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.

2.1.1 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.

2.1.2 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.

2.1.3 Feature Vector in Proposed Method

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. 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:

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

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

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.

3 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 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

4 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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