Iris Recognition Based on Ripplet Transform Feature Extraction

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Summary
A novel technique for iris recognition is proposed based on Ripplet transform. This method uses the feature given from Ripplet components. Firstly, the geometrical region of iris image is detected by segmentation using Hough transform, and then the normalization is done to produce the iris section. A set of main intrinsic directional of iris section are chosen to minimize the processing time of recognition for two-dimensional Ripplet transform. The main diagonal Ripplet components are selected. The extracted components converts to bits similar to demodulate the binary phase shift keying (BPSK) symbols. Finally, the produced iris code is generated and can be used for identification. Simulation results investigate that the proposed Ripplet technique increases the identification accuracy in comparison to fast Fourier transform (FFT) and discrete cosine transform (DCT) methods.

Kewords

Transform feature, ripplet, iris image

1. Introduction

Iris recognition has been proposed as a biometric technology for identifying people who is presented by Daugman in [1]. Iris pattern recognition is one of the important techniques in the security system because of high stability and uniqueness [2]. Identification systems made based on iris recognition uses in airports, bank services, electronic trades, personal identification etc. Several iris recognition techniques have been presented for personal identification and verification [3]. Using Eigen values achieved by principal component analysis (PCA) is proposed for personal iris analysis [4]. It was developed in [5] and improved by using classifier [6]. A shift-invariant method based on multiple bands components by 2D Gabor filter is proposed by [6]. Coherent region of iris segmentation is used to extract the color and shape information for recognition by [7]. Using complex common vector (CCV) to extract feature of iris and face for biometric recognition is proposed by [8]. Theoretical verification shows the unique common vector of CCV that can be used for fusion feature in iris and face distinctive biometric models.

In this letter, a discrimination technique proposed for iris identification base on the Ripplet transform. This method concentrates on using the Ripplet transform components in identification process. The iris section is achieved by using Hough transform. To compensate the deformations of different pupil location and various people, an accurate normalization according to the iris and pupil positions is done. A main intrinsic component set of iris section is selected in various locations to reduce the complexity and processing time of recognition. Then, two-dimensional Ripplet transform is used to catch the main diagonal of Ripplet components. The extracted components converts to bits similar to demodulate the binary phase shift keying (BPSK) symbols.

2. System model of iris segmentation and normalization

The first step, iris segmentation contains two stages, the iris position can be found by approximating its direction, then utilizing edge detection and Hough transform determines the accurate region. Subsequently, the section region is reshaped to normalized iris image. In order to smooth the image and minimize the effects of noise, a Gaussian filter $G(m,n)=\frac{1}{2\sigma^2}exp\left(\frac{-(m^2+n^2)}{2\sigma^2}\right)$ is used, therefore

$$g(m,n)=G(m,n)*f(m,n) \qquad (1)$$

where $g(m,n)$ is the smoothed eye image. The edge detection gets from the gradient of $g(m,n)$ and compare with a determined threshold. Then,

$$M(m,n)=\sqrt{g_m^2(m,n)+g_n^2(m,n)} \qquad (2)$$

The hard limited of $M(m,n)$ is

$$M_T(m,n)=\begin{cases}M(m,n) & , \quad M(m,n)\geq T_e\\ 0 & , \quad M(m,n)<T_e\end{cases} \qquad (3)$$

where T_e is the determined threshold to detect the edges. To discriminate the edges of iris and pupil sections, two thresholds T_{e_i}, T_{e_p} require. The T_{e_i} is used for iris edge and T_{e_p} is used for pupil section. Therefore,

$$M_T(m,n)=\begin{cases}M(m,n), & T_{e_p}\leq M(m,n)\leq T_{e_i}\\ 0\ , & otherwise\end{cases} \qquad (4)$$

Then circular Hough transform applied to determine the circle region. Next step is normalization. Various people and different eye moods make some deformations in iris section. So, to compensate them, an anti−clockwise unwrapped the iris loop to a rectangular block of surface with size (20x240) according to piecewise linear mapping. The distortion of the iris caused by pupil dilation can thus be reduced. Now, the normalized iris section is achieved.

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3. The Proposed method

The Ripplet transform is a new image transform that has some advantages like multi-resolution with hierarchical layer of images, good localization in spatial and frequency domains, high directionality by [9]. Ripplet (I−Type) is the extension of curvelet transform. The parabolic scaling law makes this transform flexible in different directions and scales. The discrete Ripplet transform of an $M \times N$ image $I(n_1, n_2)$ is

$$R_{j,\vec{k},l} = \sum_{n_1=0}^{M-1}\sum_{n_2=0}^{N-1} I(n_1, n_2)\overline{\rho_{j,\vec{k},l}(n_1, n_2)} \qquad (5)$$

where $\vec{k} = [k_1, k_2]$, $j, k_1, k_2, l \in Z$ and $\hat{\rho}_j(r, \omega)$ is

$$\hat{\rho}_j(r,\omega) = \frac{1}{\sqrt{c}} a^{\frac{m+n}{2n}} W(2^{-j}.r) V\left(\frac{1}{c}.2^{-\left\lfloor j\frac{m-n}{n}\right\rfloor}.\omega - l\right) \quad (6)$$

In the above relation, $W(.)$ is the radial window and $V(.)$ is the angular window which are supported by $\sum_{j=0}^{+\infty} |W(2^{-j}.r)|^2 = 1$ and $\sum_{l=-\infty}^{-\infty} \left|V\left(\frac{1}{c}.2^{-\lfloor j(1-1/d)\rfloor}.\omega - l\right)\right|^2 = 1$, respectively [9].

The wedge of frequency domain in Ripplet function is

$$H_{j,l}(r,\theta) = \left\{2^j \le |r| \le 2^{2j}, \left|\theta - \frac{\pi}{c}.2^{-\lfloor j(1-1/d)\rfloor}.l\right| \le \frac{\pi}{2}2^{-j}\right\} \quad (7)$$

where r, θ are the radial and rotation parameters in transformation. The *c* related to the high-pass band number of directions. *d* determines the direction alters across bands. It means that these two parameter controls the resolution and direction. Multi−scaling resolution and directionality changes are the vital characteristics of Ripplet transform Based on these properties the two-dimensional transform coefficients are efficiently singular in a normalized iris image. In order to achieve the accurate recognition and discrimination, the feature should be extracted from Ripplet coefficients. The Eq. (8) shows the iris component selection until the diagonal matrix for transformation is prepared. The selecting process of iris matrix is uses a main component of any sub-matrixes with the same sub-matrix.

$$\begin{pmatrix} I_{1,1} & \cdots & I_{1,N} \\ \vdots & \ddots & \vdots \\ I_{M,1} & \cdots & I_{M,N} \end{pmatrix} \exists\ D = \begin{pmatrix} I_{p,q} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & I_{g,h} \end{pmatrix} \quad (8)$$

where D is the diagonal selected component matrix with $K \times K$ size. By substituting the (8) in the (5), it gives

$$R^D_{j,\vec{k},l} = \sum_{n_1=0}^{M-1}\sum_{n_2=0}^{N-1} D(n_1, n_2)\overline{\rho_{j,\vec{k},l}(n_1, n_2)} \qquad (9)$$

The $R^D_{j,\vec{k},l}$ is a symmetric semi-diagonal matrix because D is a diagonal matrix. The three non-zero main diagonal d_1, d_2, d_3 are selected. These vectors are used for rearranged to make a greater vector $X = [d_1, d_2, d_3]$.

$$R^D_{j,\vec{k},l} = \begin{pmatrix} r_{1,1} & r_{1,2} & r_{1,3} & 0 & \cdots & 0 \\ r_{2,1} & r_{2,2} & r_{2,3} & r_{2,4} & \ddots & \vdots \\ r_{3,1} & r_{3,2} & \ddots & \ddots & \ddots & 0 \\ 0 & r_{4,2} & \ddots & \ddots & \ddots & r_{K-2,K} \\ \vdots & \ddots & \ddots & \ddots & \ddots & r_{K-1,K} \\ 0 & \cdots & 0 & r_{K,K-2} & r_{K,K-1} & r_{K,K} \end{pmatrix} \quad (10)$$

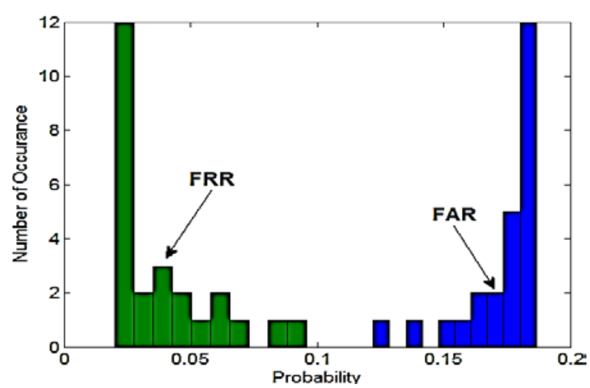
$$\hat{X}_i = \begin{cases} 1 & , \quad X_i \ge 0 \\ 0 & , \quad X_i < 0 \end{cases} \quad (11)$$

A binary iris code produced with size $3K - 3$. The matching process can be measured by the Hamming distance (HD) between the two iris bit-codes that made from Ripplet samples.

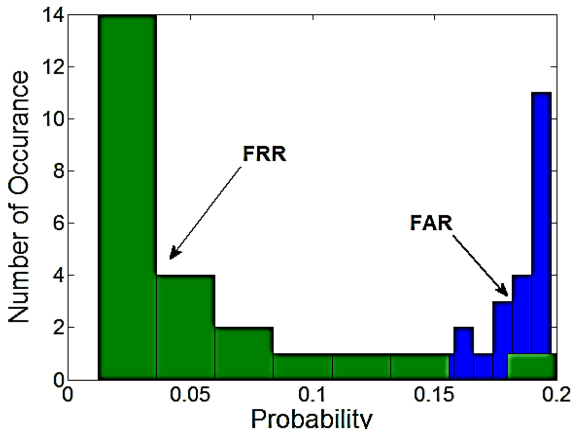
$$HD = \frac{1}{3K-3}\sum_{i=1}^{3K-3} \hat{X}_i \oplus \hat{Y}_i \qquad (12)$$

where $\hat{X}_i$ is the initial iris bit-code of sample feature vector and $\hat{Y}_i$ is the testing iris bit-code of template feature vector.

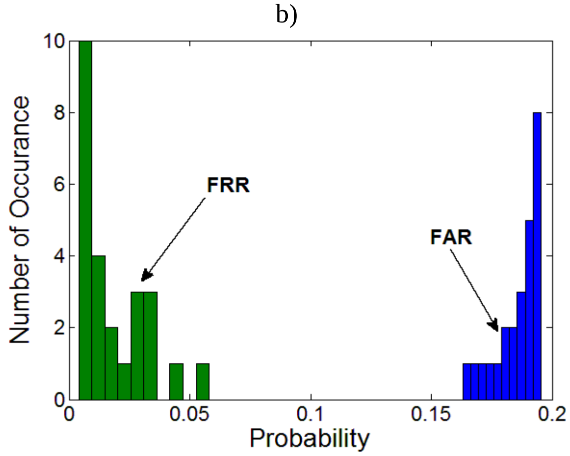
Simulations: To evaluate the performance of the proposed method, "UBIRIS.v2" [10] the iris database gathered for pattern recognition is used. This database contains 241 irises set belonging to different people and any people have five samples of different eye images in various moods. The eye images belong to large majority Latin Caucasian approximately 90% and besides black ones around 8%, and Asian people around 2%. These images were captured based on non-constrained conditions like at a determine distance, on the move, and etc, with considering the realistic noise existence. Two other methods FFT and DCT are used for comparison with proposed method. The most usual metrics that is utilized to measure the performance are false acceptance rate (FAR) and the false rejection rate (FRR). FAR is the percentage of false iris bit-codes which are wrongly accepted. FRR is the percentage of true iris bit-codes which are wrongly rejected. In our simulation the $d = 1$ and $c = 3$. All the simulations are done in the same condition.



a)



b)



c)

Fig. 1 Comparison of FAR and FRR for various methods, a) FFT, b) DCT, c) Ripplet.

Fig. 1 shows the histogram of FAR and FRR performance for FFT, DCT, and proposed Ripplet technique. It can be seen the proposed method and FFT has lower FAR and FRR in comparison to DCT method. Furthermore, the distance between the FAR and FRR of Ripplet based technique is significantly higher than FFT. However the DCT method has no distance. Fig. 2 displays the FAR versus FRR for FFT, DCT, and Ripplet base techniques. It can be seen by increasing the FRR, better discrimination is achieved and FAR becomes lower than FFT and DCT methods and finally reaches to FFT method.

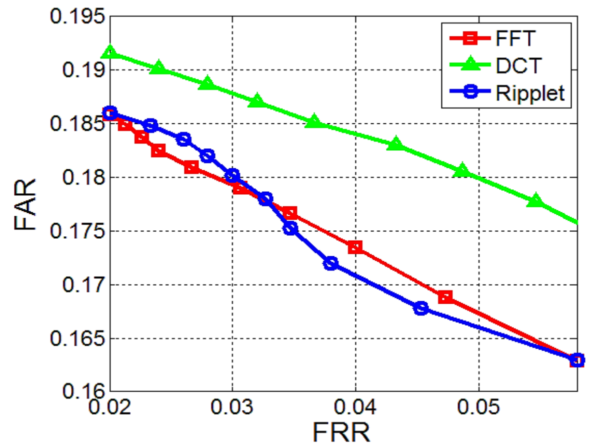


Fig. 2 Performance comparison between FFT, DCT, and Ripplet base techniques for different FAR and FRR.

4. Conclusion

A novel algorithm is proposed based on a simple fast structure for iris recognition using Ripplet transform. After iris section extracted, a diagonal matrix is made from a set of main components of sub-matrixes. The main three diagonal vectors of Ripplet coefficients are selected and rearranged to a vector. Finally, this vector produces the iris bit-codes. The proposed Ripplet method compared with FFT, and DCT transform method, achieves a higher accuracy with lower FAR and FRR. This method can use higher resolution of direction to attain better results.

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