

Comparitive Analysis of Conventional, Real and Complex Wavelet Transforms for Iris Recognition

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ABSTRACT

Iris Recognition System is a process of recognizing an individual by analyzing the random pattern of iris and comparing with database. In this paper comparative analysis is performed with wavelet transform such as 2D Discrete wavelet transform (2D-DWT), Real dual tree Discrete wavelet transform (R-DT-DWT) and Complex dual tree Discrete wavelet transform (C-DT-DWT) for iris recognition. These approaches are tested on various databases. The process starts from pre-processing. In pre-processing stage the image is enhanced, segmented and normalized. Now smoothed image is taken into consideration for feature extraction using above mentioned wavelet transforms. Finally image is applied post-classifier for reducing false rejection rate.

General Terms

Iris Recognition System, Authentication and imposter identification.

Keywords

Feature extraction, post-classifier, pre-processing and wavelet transform.

1. INTRODUCTION

Iris is the colored part of an eye, which controls light levels inside eye similar to that of aperture of camera. It is embedded with muscles that dilate and constrict pupil (which is an opening in the center of iris) size in case of dim lighting. It has a flat structure that divides the front and back portion of eye. The microscopic pigment cells called melanin are responsible for color of iris. The color, texture and patterns of iris define uniqueness of every individual. Iris Recognition System (IRS) is a biometric system providing automatic identification of an individual on the basis of physiological traits such as iris patterns and random texture which is stable throughout the life. No two irises are same, they not only differ between two identical twins but also between right and left eye of human [1].

The basic process of IRS starts with image acquisition of iris using a high resolution and professional iris camera. In cooperative environment, images are captured at short distances say 4-13cm with good illumination and near infrared which results in improvement of real-time character in iris recognition and decrease in pre-processing. But, in case of in-cooperative environment chances of rejection rate increases gradually due to matter of fact that the images captured are at different distances, motion or defocus blur,

occluders like eyelashes, eyelids, tilt of head and spectacles. Use of objective evaluation algorithm has proved to gain high

quality of iris images. Iris segmentation step involves image enhancement, preprocessing and localization. Removal of non-uniform illumination to enhance low contrast of captured image is referred as image enhancement. Reduction of salt and pepper noise using median or average filtering methods is termed as preprocessing. Iris boundary localization (both inner and outer boundaries) can be obtained using circle detector. High level iris segmentation accuracy can be obtained by removal of interference that causes grey value change in iris texture. The normalization process produces iris regions for same constant dimensions, such that two photographs of the same iris under different conditions will have same characteristic features at spatial location. Pupil dilation for varying levels of illumination can cause stretching of iris resulting in dimensional inconsistencies. Feature extraction infers to most discriminating information of iris pattern for reducing dimensionality of image retaining the original information. Finally matching the input image with templates stored in database for providing accessibility to biometric system. This study evaluates various feature extraction techniques for iris recognition [2][3].

2. PRELIMINARIES

A simple iris recognition system is as shown in the Figure 1. It includes feature extraction, similarity measurement and decision making. Given a stored database of facial images one has to train an automated system to identify or verify a person.

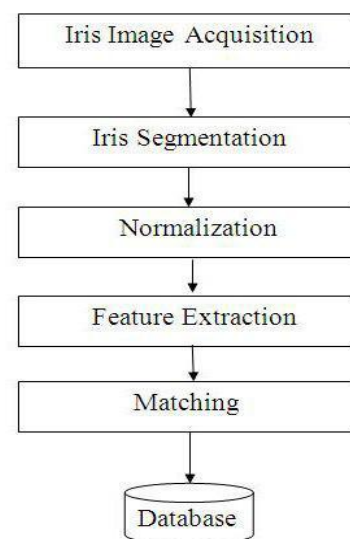


Figure 1: General Process of Iris Recognition System

2.1 Conventional Two Dimensional Discrete Wavelet Transform (2D-DWT)

A conventional two dimensional wavelet discrete transform (2D-DWT) can be considered as equivalent to filtering the input image with a bank of filters, whose impulse responses are all approximately given by scaled versions of a mother wavelet. The separable (row - column) implementation of the 2D-DWT is characterized by three wavelets,

$$\begin{aligned} \psi_1(x, y) &= \phi(x)\psi(y) && \text{(LH wavelet)} && (1) \\ \psi_2(x, y) &= \psi(x)\phi(y) && \text{(HL wavelet)} && (2) \\ \psi_3(x, y) &= \psi(x)\psi(y) && \text{(HH wavelet)} && (3) \end{aligned}$$

The LH wavelet is the product of the low - pass function along the first dimension and the high - pass (actually a bandpass) function along the second dimension. Similarly the HL and HH wavelets can be treated. In this paper, the filters given by Abdelnour et al. [4] were used.

2.2 Dual Tree Discrete Wavelet Transform (DT-DWT)

The 2-D dual-tree discrete wavelet transform (DT-DWT) of an image is implemented using two critically-sampled separable 2-D DWT's in parallel as shown in Figure 2. One of the advantages of the dual-tree DWT (DT-DWT) over separable 2D DWT is that, it can be used to implement 2D wavelet transforms that are more selective with respect to orientation. The filters used in the first stage of the dual-tree DWT are different from the filters used in the remaining stages [5]. Here, we have used *Farras* filters for the first stage and *Kingsbury's* Q-shift filters for remaining stages.

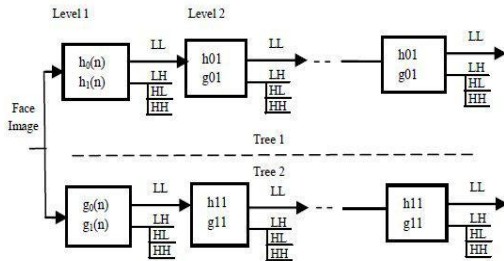


Figure 2: 2D Dual-tree discrete wavelet transform.

2.3 2D Real Dual Tree Discrete Wavelet Transform (R-DT-DWT)

In real dual-tree discrete wavelet transform (R-DT-DWT), the sum and difference for each pair of subbands gives rise to wavelets in six different directions. At each level, the wavelets are strongly oriented at angle of $\pm 15^\circ$, $\pm 45^\circ$, and $\pm 75^\circ$ as shown in Figure 3.

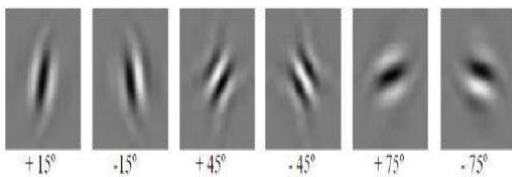


Figure 3: Six Wavelets associated with the real 2D dual-tree DWT.

2.4 2D Complex Dual Tree Discrete Wavelet Transform (C-DT-DWT)

The 2-D complex dual-tree discrete wavelet transform (C-DT-DWT) has twice as many wavelets as that of R-DT-DWT (two wavelets in each direction). The wavelets are oriented in the same six directions as those of the 2-D R-DT-DWT. In each direction, one of the two wavelets can be interpreted as the real part of a complex-valued 2D wavelet, while the other wavelet can be interpreted as the imaginary part of a complex-valued 2D wavelet as shown in the Figure 4. The extra six wavelets are obtained by swapping the low pass and high pass filter coefficients of real and imaginary trees [6].

An illustration of R-DT-DWT operated on a synthetically generated image is as shown in the Figure 5.

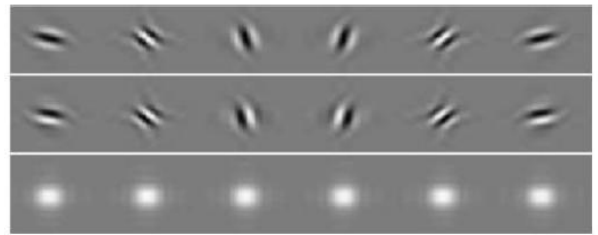


Figure 4: Impulse responses for 2-D C-DT-DWT: First row is interpreted as the real part and the second row as imaginary part of the complex wavelet. The third row shows the magnitude response.

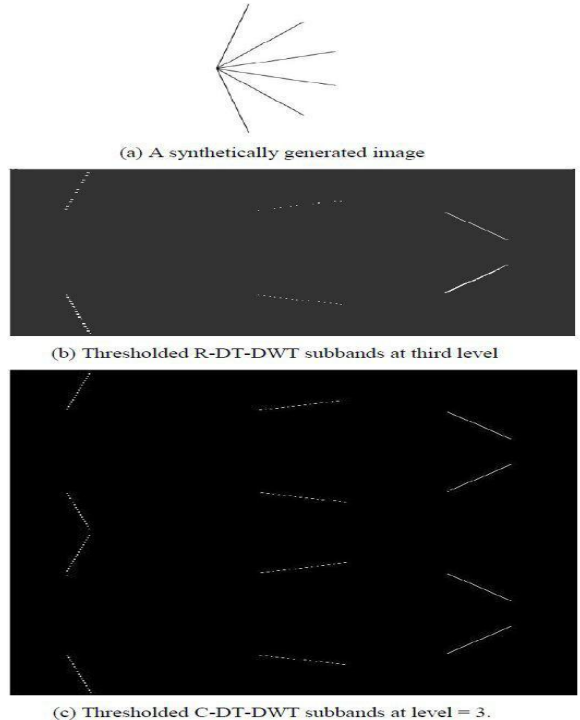


Figure 5: R-DT-DWT and C-DT-DWT subbands of a synthetically generated image.

3. EXPERIMENTAL RESULTS

3.1 Simulation Software

The software for iris recognition was built using MATLAB. This environment was chosen because it easily supports image processing, image visualization, and linear algebra. The software was tested against wide range of databases.

3.2 Feature Extraction

The feature extraction is done by applying various wavelet transforms on pre-processed iris images. The iris image is decomposed upto 3 levels using 2D-DWT, R-DT-DWT and C-DT-DWT.

3.3 Classifier

Iris-recognition algorithms have succeeded in achieving a low false acceptance rate (FAR). However, reducing the false rejection rate (FRR) remains a major challenge. In order to make the iris-recognition algorithm more robust, FRR needs to be reduced. In this work, fusion at the decision level is explored using the flexible k -out-of- n :A fused postclassifier. The value of k can be varied up to n so named as a flexible postclassifier. This proposed postclassifier works on the receiver operating characteristics curve (ROC) directly. ROC is the indirect representation of the distance scores between the test and enrolled FVs. ROC is obtained by varying threshold values of the distance scores. Equal error rate (EER) is a general optimal operating point FAR FRR that indicates threshold of the distance score. Multiple ROCs obtained from n iris regions are fused by the postclassifier in order to improve the performance. The performance of the iris-recognition system is assessed by measuring the errors made by rejecting genuine users (FRR), accepting impostor users for a given value of threshold (FAR), computing recognition accuracy, and computational complexity. The test iris is accepted if at least any out of the k -region(s) is (are) accepted (flexible k -out-of- n :A, where $k \leq n$). The details of the general k -out-of- n system for reliability analysis are given in [2].

3.4 Database

The proposed approach has been tested using UBIRIS, MMU1, CASIA-IrisV3-Interval, and IITD databases. The images have been captured with different instruments under varying conditions and different ethnicity. The UBIRIS database consists of 1877 iris images of 241 persons captured in two different sessions using a Nikon E5700 camera. The images in this database have artifacts in the form of reflection, contrast, natural luminosity, focus, and eyelids/eyelashes obstructions (leads to intraclass variations of iris pattern). The MMU1 database consists of eye images of 45 persons having 5 images of each eye. It includes a total of 450 images of 90 subjects. These images are captured with LG IrisAccess camera and contain severe obstructions by eyelids/eyelashes, specular reflection, slight occlusion of shadow of eyelids on iris, nonlinear deformation, low contrast, and illumination changes. The CASIA-IrisV3-Interval database has the left (“L”) and right (“R”) irides of 249 subjects and 396 eyeimages. The total number of images in this database is 2655. These images are captured with a self-developed iris sensor and contain eyelids/eyelashes occlusion, pupil dilation, head-tilt, specular reflection, slight shadow of eyelids on iris, etc. The IIT Delhi (IITD) database is the first Indian database consisting of a total of 1120 iris images from 224 subjects. This database consists of low resolution images and these images are captured using JIRIS, JPC1000, and a digital CMOS camera. The aforementioned artifacts are responsible for degrading the performance of the iris-recognition system on the databases. For convenience during the experimentations, 450 images of 90 subjects (5 images per subject) are randomly selected from the UBIRIS (including session1 and session2), CASIA-IrisV3-Interval (R), and IITD databases whereas all images from the MMU1 database are used. It is to be noted that MMU1 images provide less iris information than the selected UBIRIS, CASIA-IrisV3.0, and IITD images. It is observed that segmentation on some of the images of all the databases is not

accurate due to noncircular boundaries and poor transition from iris to sclera. Inaccurate segmented iris images are also used for the experimentation. Fig. 6 shows few samples of inaccurately segmented images which were used for the experimentations.

3.5 Results

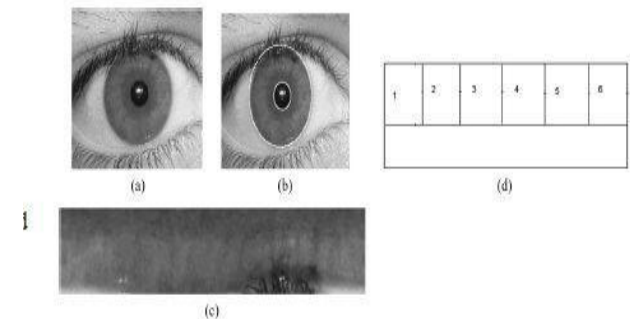


Figure 6: (a) Original eye image. (b) Segmented iris part from an eye image. (c) Normalized iris part. (d) Partitioned normalized iris.

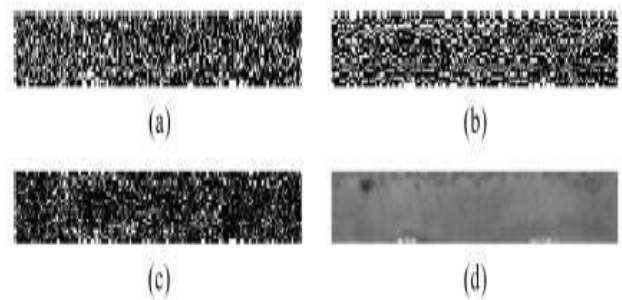


Figure 6: Decomposition using C-DT-DWT.

Table 1: Results of Iris recognition

METHOD	UBIRIS Database			MMU1 Database			Casia Iris V3.0 Database		
	FAR (%)	FRR (%)	REC. ACC. (%)	FAR (%)	FRR (%)	REC. ACC. (%)	FAR (%)	FRR (%)	REC. ACC. (%)
2D-DWT	2.25	3.25	95.12	3.98	4.56	94.25	3.45	5.36	94.25
R-DT-DWT	2.21	3.21	96.45	2.65	3.54	95.32	3.28	4.89	95.78
C-DT-DWT	1.19	2.45	98.12	3.25	3.98	98.72	3.45	4.06	97.56

3.6 Conclusion

By doing the comparative analysis with various wavelet transforms with various iris databases it is observed that, C-DT-DWT having more accuracy than the 2D-DWT and R-DT-DWT.

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5. REFERENCES

- [1] J. G. Daugman, "High confidence of visual recognition of persons by a test of statistical independence," IEEE Trans. Pattern Anal. Mach. Intell., vol. 15, no. 11, pp. 11481161, Nov 1993.
- [2] Amol D. Rahulkar and Raghunath S. Holambe "Half-Iris Feature Extraction and Recognition Using a New Class of Biorthogonal Triplet Half-Band Filter Bank and Flexible k-

- out-of-n:A Postclassi_er." *IEEE Tran. on Info. Forensic and Security*, Vol. 7, No. 1, Feb 2012.
- [3] H. Proenca and L. A. Alexandre, "Toward non cooperative iris recognition: A classification approach using multiple signatures," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 9, no. 4, pp. 607612, Jul. 2007.
- [4] A. F. Abdelnour and I. W. Selesnick. Nearly symmetric orthogonal wavelet bases. In *Proceedings of IEEE International Conference on Acoustic, Speech, Signal Processing (ICASSP)*, May 2001.
- [5] I. Selesnick, R. Baraniuk, and N. Kingsbury. The dual-tree complex wavelet transform. *IEEE Signal Process. Mag.*, 22(6):123–151, Nov. 2005.
- [6] N. Kingsbury. The dual-tree complex wavelet transform: A new technique for shift invariance and directional filters. *IEEE Digital SignalProcessing Workshop, DSP 98, paper no. 86*, August 1998.