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Wavelet Types Comparison for Extracting Iris Feature Based on Energy Compaction

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Abstract. Human iris has a very unique pattern which is possible to be used as a biometric recognition. To identify texture in an image, texture analysis method can be used. One of method is wavelet that extract the image feature based on energy. Wavelet transforms used are Haar, Daubechies, Coiflets, Symlets, and Biorthogonal. In the research, iris recognition based on five mentioned wavelets was done and then comparison analysis was conducted for which some conclusions taken. Some steps have to be done in the research. First, the iris image is segmented from eye image then enhanced with histogram equalization. The features obtained is energy value. The next step is recognition using normalized Euclidean distance. Comparison analysis is done based on recognition rate percentage with two samples stored in database for reference images. After finding the recognition rate, some tests are conducted using Energy Compaction for all five types of wavelets above. As the result, the highest recognition rate is achieved using Haar, whereas for coefficients cutting for $C(i) < 0.1$, Haar wavelet has a highest percentage, therefore the retention rate or significan coefficient retained for Haar is lower than other wavelet types (db5, coif3, sym4, and bior2.4)

Keywords: iris feature, energy compaction, recognition rate, wavelet coefficient.

1. Introduction

Humans as individuals, have unique characteristics and distinctive. These characteristics can be used to recognize or identify persons. This is known as biometric recognition. Iris is the part of the circle around eye pupil. Although iris has a relatively narrow region compared with entire area of the human body, iris has a very unique pattern, different in each individual and the pattern will remain stable. For those reasons, iris can be used as the basis for the recognition in biometrics.

Many algorithms have been applied as a method of iris recognition, such as PCA (Principal Component Analysis), ICA (Independent Component Analysis), Gabor-Wavelet algorithm [6], characterizing Key Local Variation, Laplace Pyramid, Gray Level Co-ocurrence Matrix (GLCM) [7] and others. Haar wavelet transform as a method to analyze the texture is still rarely used as a feature extractor on iris pattern. In this research, texture-based recognition methods were analyzed using the method of characterizing the transforms of Haar, Daubechies, Coiflets, Symlets, and Biorthogonal wavelets, which then the comparison of these five types of wavelets based on energy compaction will be conducted. The kind of research has not been done by other researchers, for which this research can show its novelty aspect. The previous research was done by the author and published in [7].

In order not to deviate far from the problems exist, the research problems are limited as follows:
1. Iris image used is the image that has been available, which is using the database of CASIA V1.0.
2. Research is focused on the compaction energy of Haar Daubechies (db5), Coifles (coif3), Symlets (sym4), and Biorthogonal (bior2.4) wavelets transform as feature extractor and feature used is energy
3. Recognition method used is the normalized Euclidean distance method.

The purpose of doing this research is to analyze some types of wavelets that can perform a comparative analysis on iris recognition rate using the Haar, Daubechies (db5), Coifles (coif3), Symlets (sym4), and Biorthogonal (bior2.4) wavelets with Energy Compaction calculations. Therefore those results then are compared and analyzed against their recognition rates. While the motivation of the research is that the iris can be used as an organ in biometric system with higher accuracy level and the fact that, up until now, there is no adequate research done for comparing these five wavelets mentioned above to extract iris features based on iris compaction.

Iris can serve as the basis for biometric systems. Each iris has a texture that is very detailed and unique to each person and remain stable for decades. The eye cannot be altered through surgery without causing any damage to eyesight. Fig.1 shows the anatomy of the eye, and examples of human iris [2].

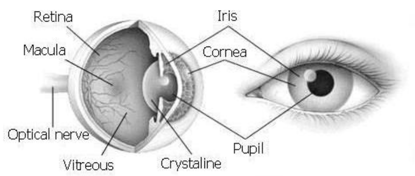

Figure 1. Anatomy of eyes and example of iris region.

The advantages of using the iris for reliable identification system are [3] as follows.
1. Iris is insulated and shielded from the outside environment.
2. In the iris, it is not possible to do some surgeries without causing defects in the eye.
3. Iris has a physiological response to light, which allows testing of the natural use of the possibility of fraud and faked eye lenses and so forth.

Wavelets are mathematical functions that satisfy certain requirements are able to perform the decomposition of a function [5]. Hierarchically, wavelet is used to represent data or other functions. Wavelet can be used to describe a model or the original image into a mathematical function regardless of the shape of the model in the form of image, a curve or a plane. Wavelet transform is a function that converts the signals from region to region the frequency or time scale. The most appropriate wavelet transform used in image processing because there is not much information is lost during the reconstruction.

Wavelet is a base derived from a wavelet basis function which is also said to be a scaling or scaling function. Scaling function has properties which can be assembled from a number of copies that have been dilated, translated and scaled. This function is derived from the dilation equation, which is considered as the basis of wavelet theory.

The wavelet decomposition can be continued using lowpass-lowpass (LL) as its input for getting next decomposition stages. Figure 4 shows a decomposition image from level 1 until level 3. Maximum level of decomposition in image processing using wavelet (except biorthogonal wavelets) can be formulated as indicated in Eq. (1) [4]. This equation is derived from how many times we can divide the data length (i.e. the minimum size of either horizontal or vertical pixels of an image) by number of 2 (two).

$$\text{Level}_{max} = \frac{\log(\text{datalength}/(\text{filterlength-1}))}{\log(2)} \tag{1}$$

Energy is defined as the sum of the squares of the values. So the energy of an image is the sum of the squares of the pixel values, the energy in the wavelet transform of an image is the sum of the squares of the transform coefficients. During wavelet analysis the energy of a signal is divided between approximation and details signals but the total energy does not change. During compression, however, energy is lost because thresholding changes the coefficient values and hence the compressed version contains less energy.

The compaction of energy describes how much energy has been compacted into the approximation signal during wavelet analysis. Compaction will occur wherever the magnitudes of the detail coefficients are significantly smaller than those of the approximation coefficients. Compaction is important when compressing signals because the more energy that has been compacted into the approximation signal the less energy can be lost during compression.

Energy compaction can be obtained from the number of least significant coefficients, for which those coefficients can be cut or removed. In this case, it can be said that insignificant coefficients mean that there are zero valued coefficients and which can be seemed less enough to be cut or removed. In energy compaction, the term of 'retention' is also used. Retention indicates coefficient values which can be retained in calculation.

2. Research Method

Method of iris recognition system can be depicted in a flowchart which is shown in Figure 2, as an enhancement procedure introduced by Daugman [2], which is improved by Isnanto, *et al.* [7]. Broadly explained, the processes can be classified into some steps which can be depicted in pseudocodes below.

```
PROCEDURE Iris_Recognition

CASE wavelet_types
   1: Haar
   2: db5
   3: coif3
   4: sym4
   5: bior2.4

INPUT OriginalEyeImage
   DO segmenting OriginalEyeImage to separate IrisImage from its OriginalEyeImage
   DO normalizing the IrisImage for getting NormalizedIrisImage
   MinEuclideanDistance := 100 % impossible distance in the research
   FOR i = 1 TO NumberOfStoredImage
        DO extracting the features using CASE 1,2,3,4,5; OUTPUT feature(CASE)
        CALCULATE EuclideanDistance(feature(CASE) , feature(i))
        IF EuclideanDistance(feature(CASE) , feature(i)) < MinEuclideanDistance ...
        ... THEN MinEuclideanDistance = EuclideanDistance(feature(CASE),feature(i))
        DO plotting graphics of correlation between the number of coefficient...
        ...(x-axis) against coefficients values (y-axis) for CASE 1,2,3,4,5
        CALCULATE energy compaction with some coefficient values of CASE...
        ...1,2,3,4,5 which results of retention for CASE 1,2,3,4,5

   NEXT i
OUTPUT recognized as feature which has MinEuclideanDistance
ANALYZE the results of PROCEDURE executes
```

Iris image used is the image from database of CASIA V1.0 – Portions of the research in this paper use the CASIA-IrisV1 collected by the Chinese Academy of Sciences' Institute of Automation (CASIA) – and iris images captured using Irdosoft 4.0 camera [1].

In database, pupil circle and iris circle are not always perfect circle for which for getting only iris needs a complex computation. For simplifying the computation, it is assumed that pupil as well as iris has a perfect-circle form. First step is finding pupil circle, centre point and its radius. Some subprocesses have to be done are thresholding, smoothing, and obtaining the centre point of pupil and its radius using Circular Hough Transform.

Pupil and iris images which are circle-form with their diameters are varied, are then converted into a fix-sized rectangular form. The size is 60×512 pixels. This conversion also for simplifying both coding as well as computation.

The presence of eyelids and eyelashes also can can disrupt the process of iris recognition and reduce the level of accuracy. Therefore, not all parts of the iris is taken. For the iris image of CASIA, the top part of the image is cut so that the bottom of the iris of the eye are taken. Image size is 60 × 384 pixels. Iris image which has been converted into a rectangular shape has a low contrast level so that the resulting level of accuracy is less good. Therefore, the contrast then enhanced using adaptive histogram equalization. First, image is is split into 3 × 12 parts of each section measuring 20 × 32 pixels. The purpose is to obtain images with good contrast but will not damage the overall image quality.

Iris image is split into 6 slices. Feature extraction is per-formed to all images which have been split before using 5 (five) wavelet types. Features obtained are energies of E_a, E_h, E_v, dan E_d.

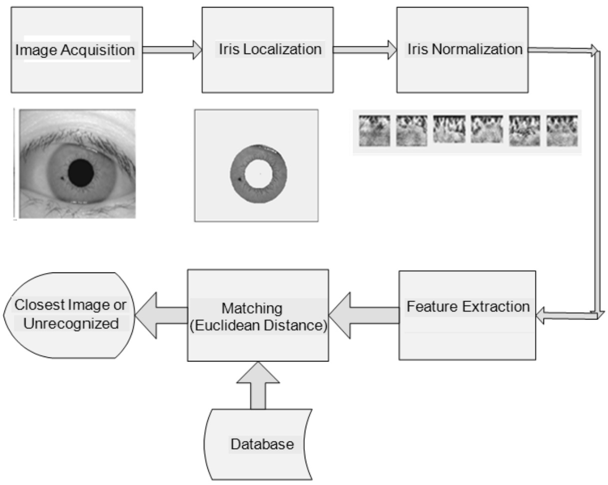

Figure 2. Flowchart of iris recognition system using feature extraction from different wavelets.

3. Results and Discussion

3.1 Recognition Testing
The purpose of recognition test is to obtain what level of recognition rate of the system, when different decomposition levels are used from 5 types of wavelet filter, i.e. Haar, db5, coif3, sym4, and bior2.4.

Some tests were conducted for 128 images, originated from 64 persons. While the stored images in database are 2 samples for each person. Maximum decomposition levels for Haar, db5, coif3, sym4, and bior2.4 are 5, 2, 1, 3, and 2, respectively. From all allowed decomposition level tests, it can be inferred that: (a) The best recognition level is 84.375% which is achieved by Haar with decomposition level 3. (b) The decreasing order of average of recognition rate is: Haar, sym4, db5, and bior2.4 for the least. Table 1 shows all wavelet tests up to the maximum level achieved. From this table, it can be shown that the higher level of decomposition, the recognition level tends to be better.

Table 1. Recognition rate from different decomposition level.

Decomposition Level	Recognition Rate (%)				
	Haar	**db5**	**coif3**	**sym4**	**bior2,4**
1	68,750	38,231	25,000	42,188	42,969
2	76,563	68,750	-	60,938	60,156
3	84,375	-	-	65,625	-
4	83,594	-	-	-	-
5	83,594	-	-	-	-
Average of recognition rate (%)	**79,375**	**53,491**	**25,000**	**56,250**	**51,563**

3.2 Energy Compaction Testing

In this test, wavelet coefficient threshold *C*(*i*) of 0.001 and 0.1 respectively are applied. We can use 2 (two) scenarios to analyze the comparison of energy compaction for 5 types of wavelet tested. *First*, we can visually analyze from graphics which depicting the relationship between *i*-th coefficient and its corresponding wavelet coefficient value *C*(*i*). Figures 3-7 show these relationships and we therefore can observe the existing trends of the graphics. It can be shown that wavelet coefficient distribution of Haar wavelet gives the best retention because of most coefficients have a small value, and the first values are very high. It means that the approximation values are high enough if compared with detail values. *Second*, we can use the retention concept which means coefficient values which can be retained in calculation. The more coefficients can be cut or removed, the less retention can be produced. The retention is better when its value is lower. Table 2 and Table 3 depict the retention level for threshold value 0.001 and 0.1, respectively.

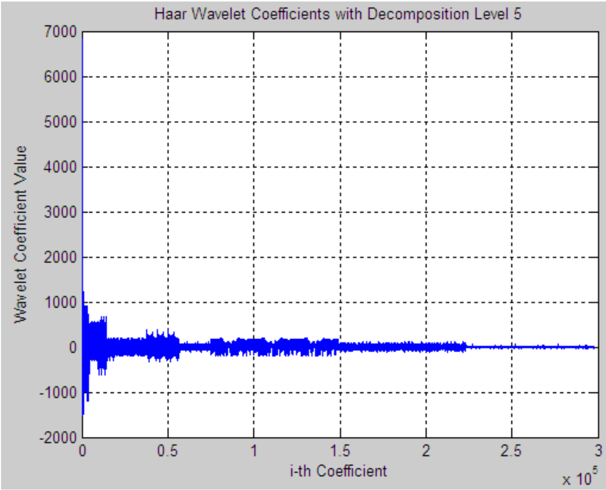

Figure 3. Wavelet coefficient values for Haar, decomposition level 5.

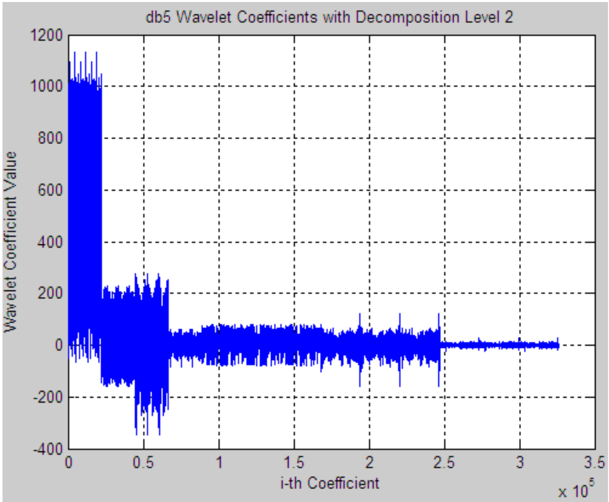

Figure 4. Wavelet coefficient values for db5, decomposition level 2.

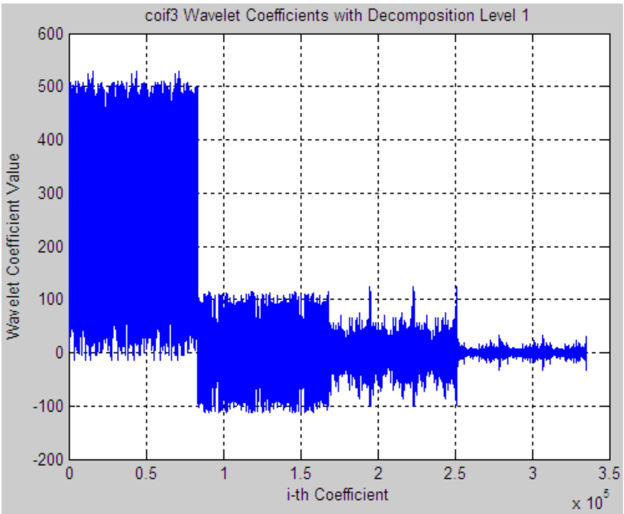

Figure 5. Wavelet coefficient values for coif3, decomposition level 1.

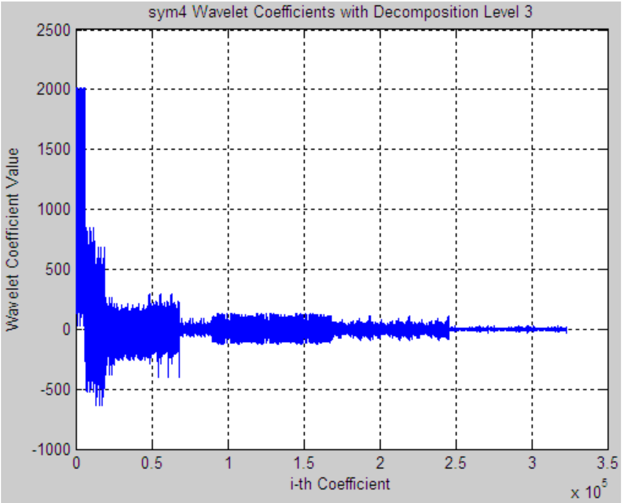

Figure 6. Wavelet coefficient values for sym4, decomposition level 3.

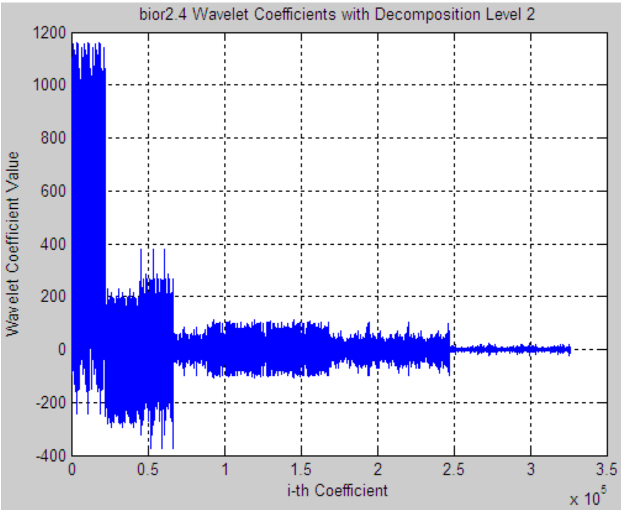

Figure 7. Wavelet coefficient values for bior2.4, decomposition level 2.

Table 2. Energy Compaction with Threshold C(i) > = 0.001

Wavelet	Energy compaction	Decomposition Level					Average	
		1	2	3	4	5		
Haar	Retention (%)	58.7	49.3	46.8	46.3	46.1	49.44	
	Removed (%)	41.3	50.7	53.2	53.7	53.1	*50.40*	Highest
db5	Retention (%)	63.1	54.2	-	-	-	58.65	
	Removed (%)	36.9	45.8	-	-	-	41.35	
coif3	Retention (%)	62.3	-	-	-	-	62.30	
	Removed (%)	37.7	-	-	-	-	37.70	
sym4	Retention (%)	62.5	53.3	51.0	-	-	55.60	
	Removed (%)	37.5	46.7	49.0	-	-	44.40	
bior2.4	Retention (%)	60.4	51.3	-	-	-	55.85	
	Removed (%)	39.6	48.7	-	-	-	44.15	

Table 3. Energy Compaction with Threshold C(i) > = 0.1

Wavelet	Energy compaction	Decomposition Level					Average	
		1	2	3	4	5		
Haar	Retention (%)	58.8	49.3	46.9	46.3	46.1	49.48	
	Removed (%)	41.2	50.7	53.1	53.7	53.9	*50.52*	Highest
db5	Retention (%)	60.9	50.9	-	-	-	55.90	
	Removed (%)	39.1	49.1	-	-	-	44.10	
coif3	Retention (%)	59.8	-	-	-	-	59.80	
	Removed (%)	40.2	-	-	-	-	40.20	
sym4	Retention (%)	60.0	50.7	48.4	-	-	53.03	
	Removed (%)	40.0	49.3	51.6	-	-	46.97	
bior2.4	Retention (%)	59.1	49.8	-	-	-	54.45	
	Removed (%)	40.9	50.2	-	-	-	45.55	

For removing the coefficients $C(i) < 0.1$ as well as for $C(i) < 0.001$, Haar wavelet has the highest percentage of coefficients removed, there are 50.54% and 50.52% for which significant coefficients (retention) are less than other wavelets (db5, coif3, sym4, dan bior2.4).

According the previous mentioned reason, based on recognition level as well as its energy compaction, Haar wavelet has good performance for extracting the iris feature when compared with other wavelets. Based on recognition level, Haar indicates the highest level of recognition, i.e. 79.38%. Whereas, according to energy compaction, Haar also indicates the highest percentage of coefficients removed as mentioned in previous paragraph.

4. Conclusion

From results of tests and analysis, it can be concluded that: The higher level of decomposition, the recognition level tends to be better. Applying Haar wavelet produces the highest recognition rate in all allowed decomposition level (from level 1 up to 5). On the other hand, for removing the coefficients $C(i) < 0.1$ as well as for $C(i) < 0.001$, Haar wavelet has the highest percentage of coefficients removed, for which significant coefficients (retention) are less than other wavelets (db5, coif3, sym4, and bior2.4). Therefore, from the previous mentioned, based on recognition level as well as its energy compaction, Haar wavelet has good performance for extracting the iris feature when compared to other wavelets.

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References

[1] CASIA, *Iris Image Database*, www.sinobiometrics.com.

[2] Daugman, J. "How Iris Recognition Works", IEEE Transaction on Circuits and system for Video Technology, vol 14, no.1, January 2004.

[3] Daugman, J. "*Iridology*", http://www.cl.cam.ac.uk/ users/jgd1000/, Februari, 2009.

[4] Misiti, M., Y. Misiti, G. Oppenheim, and J.M. Poggi, *Wavelet Toolbox For Use with Matlab*, User's Guide Version 3, The Math Works, Natick, MA, 2004.

[5] Moreno, R.P. and A. Gonzaga, *Features Vector For Personal Identification Based On Iris Texture*. Departamento de Engenharia Elétrica - EESC – USP, Februari, 2009.

[6] Rahmawati, I., "*Pemampatan Citra Digital Dengan Wavelet Paket*", Skripsi S-1, Universitas Diponegoro, 2007.

[7] Isnanto, R.R., Widodo, T.S., and Suhardjo, *Implementation of Gray Level Cooccurrence Matrix (GLCM) for Human Iris Recognition System*, Proceedings of Conference on Information Technology and Electrical Engineering 2010 (CITEE 2010), Yogyakarta, Indonesia, ISSN: 2085-6350, pp. 95-101