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Performance Evaluation of Filters of Discrete Wavelet Transforms for Biometrics

Priya Bhirud*, Prof.Nandana Prabhu**
* Department of Computer Engineering, KJSCE,Mumbai University
** Department of Information Technology, KJSCE,Mumbai University

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ABSTRACT

Biometrics associated with automated methods of identifying a person or verifying the identity of a person based on physiological or behavioral characteristics. Commonly used biometric features are facial features, fingerprints, voice, facial thermo grams, iris, posture/gait, palm print, hand geometry etc. Compared with other biometric characteristics iris is the most stable and hence the most reliable biometric characteristic over the period of a lifetime. This proposed work provides comparative study of various filters of Wavelet Transforms in terms of size and PSNR of images

Corresponding Author:

Priya Bhirud,
Department of Computer Engineering,
Mumbai University.
Email : pandu@yahoo.co.in

1. INTRODUCTION

Biometrics recognizes individuals based on the features derived from their Physiological and behavioral characteristics. Biometric systems provide reliable way of recognition to confirm the individual identity. A higher degree of confidence can be achieved by using unique physical or behavioral characteristics to identify a person [1].

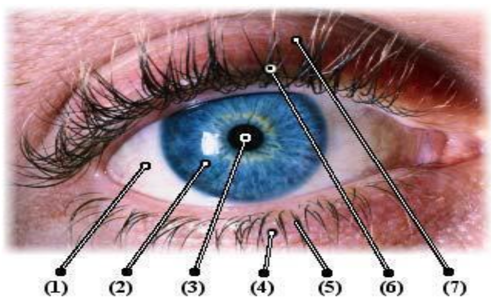

Figure. 1 Human eye

Due to the vibrant color and texture of the iris it is typically the most visible and distin-guishable part of the human eye.Human eye shows (1) is sclera, (2) iris, (3) pupil, (5, 6) eyelashes and (4, 7) eyelids.

Still there are certain issues particularly the security issues of both biometric system and biometric data. As biometric template are stored in the centralized database, due to security threats biometric template may be modified by attacker [6]. If biometric template is altered or modifies authorized user will not be allowed to access the resource. Because of these causes researches have been made to protect the biometric data and template in the system by using cryptography, stenography and watermarking.

So to implement security for iris images its embedded in cover image/images .for this reason size of iris image should be 40% of cover image .This is achieved by decomposing Iris image by wavelet transform and then embedded into cover image. Discrete Wavelet transform have various filers associated with it such as HAAR filter, Biorthogonal filter, Coif lets, Daubechies filter. In the proposed comparison of performance of these filters with respect to Iris image has been carried out for obtaining best filter can be used to embed in cover image.

The paper is organized as follows: Section 2 discusses the Wavelet Transforms .Section 3 explains what are different types of filters associated with DWT(Discrete Wavelet Transform). Section 4 explains the proposed method. The experiments conducted and simulation results are presented in section 5. Finally, conclusions are given in section 6.

2. WAVELET TRANSFORM

There are many different types of wavelets transform. Most of data analysis applications are using Continuous-time wavelet transforms (CWT). However, the most popular type which affected the properties of many real signals is discrete wavelet transform (DWT) [13]. The wavelet transform is similar to the Fourier transform with a completely different merit function. The main difference in both is Fourier transform decomposes the signal into sines and cosines, i.e. the functions localized in Fourier space; in contrast with that wavelet transform uses functions that are localized in both the real and Fourier space. Generally, the wavelet transform can be expressed by the following equation:

$$F(a,b) = \int_{-\infty}^{\infty} f(x)\, \psi^{*}_{(a,b)}(x)\, \mathrm{d}x$$

Where the * is the complex conjugate symbol and function ψ is some function. This function can be chosen arbitrarily provided that obeys certain rules.

The Wavelet transform is in fact an infinite set of various transforms, depending on the merit function used for its computation. The division based on the wavelet orthogonality is to use *orthogonal wavelets* for discrete wavelet transform development and *non-orthogonal wavelets* for continuous wavelet transform development. These two transforms have the following properties:

1. The discrete wavelet transform returns a data vector of the same length as the input is. Usually, even in this vector many data are almost zero. This corresponds to the fact that it decomposes into a set of wavelets (functions) that are orthogonal to its translations and scaling. Therefore we decompose such a signal to a same or lower number of the wavelet coefficient spectrum as is the number of signal data points. Such a wavelet spectrum is very good for signal processing and compression, for example, as we get no redundant information here.
2. The continuous wavelet transform in contrary returns an array one dimension larger that the input data. For a 1D data we obtain an image of the time-frequency plane. We can easily see the signal frequencies evolution during the duration of the signal and compare the spectrum with other signals spectra. As here is used the non-orthogonal set of wavelets, data are correlated highly, so big redundancy is seen here. This helps to see the results in a more humane form.

2.1. Continuous Wavelet Transform

Continuous wavelet transform (CWT) is an implementation of the wavelet transform using arbitrary scales and almost arbitrary wavelets. The wavelets used are not orthogonal and the data obtained by this transform are highly correlated. For the discrete time series we can use this transform as well, with the limitation that the smallest wavelet translations must be equal to the data sampling. This is sometimes called Discrete Time Continuous Wavelet Transform (DT-CWT) and it is the most used way of computing CWT in real applications

A continuous wavelet transform (CWT) is used to divide a continuous-time function $x(t)$ into wavelets. Unlike Fourier transform, the continuous wavelet transform possesses the ability to construct a time-frequency representation of a signal that offers very good time and frequency localization. In mathematics, the continuous wavelet transform of a continuous, square-integrable function at a scale $a > 0$ and translational value $b \in \mathbb{R}$ is expressed by the following integral.

$$X_w(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^* \left(\frac{t-b}{a}\right) dt$$

Where Ψ (t) is a continuous function in both the time domain and the frequency domain called the mother wavelet and $*$ represents operation of complex conjugate

In principle the continuous wavelet transform works by using directly the definition of the wavelet transform, i.e. we are computing a convolution of the signal with the scaled wavelet. For each scale we obtain by this way an array of the same length *N* as the signal has. By using *M* arbitrarily chosen scales we obtain a field $N \times M$ that represents the time-frequency plane directly. The algorithm used for this computation can be based on a direct convolution or on a convolution by means of multiplication in Fourier space (this is sometimes called Fast Wavelet Transform).

The choice of the wavelet that is used for time-frequency decomposition is the most important thing. By this choice we can influence the time and frequency resolution of the result. We cannot change the main features of WT by this way (low frequencies have good frequency and bad time resolution; high frequencies have good time and bad frequency resolution), but we can somehow increase the total frequency of total time resolution. This is directly proportional to the width of the used wavelet in real and Fourier space. If we use the Morlet wavelet for example (real part – damped cosine function) we can expect high frequency resolution as such a wavelet is very well localized in frequencies. In contrary, using Derivative of Gaussian (DOG) wavelet will result in good time localization, but poor one in frequencies.

2.2. Discrete Wavelet Transform

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. As with other wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time).

The discrete wavelet transform (DWT) is an implementation of the wavelet transform using a discrete set of the wavelet scales and translations which follows some defined rules. This transform decomposes the signal into mutually orthogonal set of wavelets, which is the main difference from the continuous wavelet transform (CWT), or its implementation for the discrete time series sometimes called discrete-time continuous wavelet transform (DT-CWT).The wavelet can be constructed from a scaling function which describes its scaling properties. The restriction that the scaling functions must be orthogonal to its discrete translations implies some mathematical conditions on them which are mentioned everywhere, e.g. the dilation equation

$$\phi(x) = \sum_{k=-\infty}^{\infty} a_k \phi(Sx - k)$$

where S is a scaling factor (usually chosen as 2).The area between the function must be normalized and scaling function must be orthogonal to its integer translations, i.e.

$$\int_{-\infty}^{\infty} \phi(x)\, \phi(x+l)\, \mathrm{d}x = \delta_{0,l}$$

After introducing some more conditions (as the restrictions above does not produce unique solution) results can be obtained of all these equations, i.e. the finite set of coefficients ak that define the scaling function and also the wavelet. The wavelet is obtained from the scaling function as N where N is an even integer. The set of wavelets then forms an orthonormal basis which we use to decompose the signal. Note that usually only few of the coefficients are nonzero, which simplifies the calculations.

3. FILTERS OF DISCRETE WAVELET TRANSFORM

There are various filters associated with Discrete Wavelet Transform. We outline the basic development of discrete wavelet transformations as follows.

3.1. HAAR Transform

Any discussion of wavelets begins with Haar wavelet, the first and simplest. Haar wavelet is discontinuous, and resembles a step function. We motivate this transformation as follows:

Suppose we wish to transmit a list (vector) of N numbers, N even, to a friend via the Internet. To reduce transfer time, we decide to send only a length N/2 approximation of the data. One way to form the approximation is to send pair wise averages of the numbers. For example, the vector [6,12,15,15,14,12,120,116] T can be approximated by the vector $[9,15,13,118]^T$. Of course, it is impossible to determine the original N numbers from this approximation, but if, in addition, we transmit the N/2 averaged directed distances, then our friend could completely recover the original data. For our example, the averaged directed distances are $[3,0,-1,-2]^T$.We define the one–dimensional discrete Haar wavelet transformation as the linear transformation.

$x \rightarrow [a/d]$

$a_k = (x_{2k-1}+x_{2k})/2,$

$d_k = (-x_{2k-1}+x_{2k})/2,$

Following figure gives behavior of wavelet function [11]

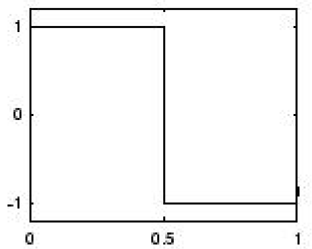

Figure 2. Wavelet Function

3.2. Daubechies Orthogonal Filter

The most commonly used set of discrete wavelet transforms was formulated by the Belgian mathematician Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale. In her seminal paper, Daubechies derives a family of wavelets, the first of which is the Haar wavelet. Interest in this field has exploded since then, and many variations of Daubechies' original wavelets were developed [3].

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets — thus making discrete wavelet analysis practicable. The names of the Daubechies family wavelets are written dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet.

3.3. Biorthogonal Filter

This family of wavelets exhibits the property of $\phi, \tilde{\phi}$ linear phase, which is needed for signal and image reconstruction. By using two wavelets, one for decomposition (on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived.

In the Biorthogonal case [5], there are two scaling functions , which may generate different multiresolution analyses, and accordingly two different wavelet functions $\psi, \tilde{\psi}$. So the numbers M and N of coefficients in the $\sum_{n\in\mathbb{Z}} a_n \tilde{a}_{n+2m} = 2\cdot\delta_{m,0}$ scaling sequences $a, \tilde{a}$ may differ. The scaling sequences must satisfy the following Biorthogonality condition.

$$b_n = (-1)^n \tilde{a}_{M-1-n} \qquad (n = 0, \ldots, N-1)$$
$$\tilde{b}_n = (-1)^n a_{M-1-n} \qquad (n = 0, \ldots, N-1)$$

Then the wavelet sequences can be determined as

4. PROPOSED WORK

In the Proposed work suggested by this paper, Iris image which is to be embed in cover image for security will be decomposed by wavelet transform using various filters like Daubechies Orthogonal filter, HAAR filter and Biorthogonal filter using DWT .For performance evaluation Comparison of Gray scale Iris image with wavelet decomposed Iris is performed.

This comparison will be carried out on basis of two parameters
1. Number of pixels
2. PSNR (peak signal to noise ratio)

5. RESULT

The results obtained by using Phoenix database[9] and Kekare's database[10] are as follows.

Table 1. Comparison table for filters.

Number	**Original Gray scale Iris image (No. of pixels)**	**Haar Filter**		**Biorthogonal Filter**		**Daubechies Filter**	
		No. of Pixels	**PSNR**	**No. of Pixels**	**PSNR**	**No. of Pixels**	**PSNR**
1	**Left Iris(phoenix)**	288*384 (110592)	32.8163	295*391 (115345)	34.4071	290*386 (111940)	33.1804
2	**Right Iris(phoenix)**	288*384 (110592)	34.5965	295*391 (115345)	36.3271	290*386 (111940)	34.9104
3	**Iris from kenkare's database**	379*288 (109152)	37.5912	388*295 (114460)	39.0144	381*290 (110490)	37.9130

6. CONCLUSION

From the work that has been accomplished above results are obtained and it can be concluded that using various filters for wavelet transforms, images of different size could be obtained. So we get images in reduced number of pixels as compared to original iris image, while maintaining quality of image using HAAR transform. HAAR transform gives average value of PSNR along with less number of pixels. Because of this reason in following future scope of project HAAR transform will be used to reduce Iris size then it will get embedded in cover image.

REFERENCES

[1] A.Jain, R. Bolle and S. Pankanti,."*Biometrics: Personal Identification in a Networked Society*", 1999eds. Kluwer,

pp 276-284.
[2] Alfredo Mertins .”*Signal Processing; Wavelets, Filter Banks, TimesFrequency Transforms and Applications*” 1999,Wollongong University.
[3] Akansu, Ali N.; Haddad, Richard A. “*Multiresolution signal decomposition: transforms, subbands, and Wavelets*”1992,Boston,MA,Acedemic Press,ISBN 78-0-12-047141-6.
[4] Catherine Bénéteau and Patrick J. Van Fleet.”*Discrete WaveletTransformations & undergraduate Education*”May2011 Notices of AMS Volume 58, Number 5.
[5] Stéphane G. Mallat .” *A Wavelet Tour of Signal Processing.*”1999 Academic Press ISBN 978-0-12-466606-1.
[6] Mrs.D.Mathivadhani, Dr.C.Meena .”*BIOMETRIC BASED AUTHENTICATION USING WAVELETS AND VISUAL CRYPTOGRPHY* “2011,978-1-4577-0590-8/11/$26.00. IEEE.
[7] Akansu, Ali N.; Haddad, Richard A. “ *Multiresolution signal decomposition: transforms, subbands, and wavelets”* ,1992 Boston,MA:Academic Press,ISBN 978-0-12-047141-6.
[8] Yunhong Wang, Yong Zhu, Tieniu Tan,.”B*IOMETRIC PERSONAL IDENTIFICATION BASED ON IRIS PATTERN*”ACTA AUTOMATICA SINICA,2002,28(1):1-10(In Chinese)
[9] Kekare’s Iris database.
[10] Digital Image processing Using Matlab(Gonzalez).
[11] Matlab Mathworks.com.
[12] A. Bultheel: Bull. Belg. Math. Soc.: (1995) 2.
[13] S. G. Chang, B. Yu, M. Vetterli: IEEE Trans. Image Processing (2000) 9 p.1532.
[14] S. G. Chang, B. Yu, M. Vetterli: IEEE Trans. Image Processing (2000) 9 p. 1522..