# IRIS PATTERN RECOGNITION USING COMPLEX WAVELET AND WAVELET PACKET TRANSFORM

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**Abstract**

A new iris recognition system based on Wavelet Packet Analysis and Morlet wavelet is described. Morlet wavelet calculations are easy compared to Gabor wavelets. Moreover Gabor wavelet based iris recognition system is patented which blocks its further development. The most unique phenotypic feature visible in a person's face is the detailed texture of each eye's iris. The visible texture of a person's iris is encoded into a compact sequence of 2-D Morlet wavelet coefficients, which generate an "iris code" of 2025-bits. Two different iris codes are compared using exclusively OR comparisons. In this paper, we propose a novel multi-resolution approach based on Wavelet Packet Transform (WPT) for iris texture analysis and recognition. The development of this approach is motivated by the observation that dominant frequencies of iris texture are located in the low and middle frequency channels. With an adaptive threshold, WPT sub images coefficients are quantized into 1, 0 or -1 as iris signature. This signature presents the local information of different irises. The signature of the new iris pattern is compared against the stored pattern after computing the signature of new iris pattern and identification is performed.

**Keywords**

Biometrics, Iris pattern, Morlet wavelet, Symlets wavelet, Wavelet Packet Transform.

## 1. Introduction

The word iris is generally used to denote the colored portion of the eye. It is a complex structure comprising muscle, connective tissues and blood vessels [1]. The image of a human iris thus constitutes a plausible biometric signature for establishing or confirming personal identity. Further properties of the iris that makes it superior to fingerprints for automatic identification systems include, among others, the difficulty of surgically modifying its texture without risk, its inherent protection and isolation from the physical environment, and it's easily monitored physiological response to light. Additional technical advantages over fingerprints for automatic recognition systems include the ease of registering the iris optically without physical contact beside the fact that its intrinsic polar geometry does make the process of feature extraction easier.

J.Daughman proposed the first successful implementation of iris recognition system in 1993[3]. This work though published more than 15 years ago still remains valuable since because it provides solutions for each part of the system. It is worth mentioning that most systems implemented today are based on his work. They are based on Gabor wavelet analysis [1] [2] [3] in order to extract iris image features. It consists in convolution of image with complex Gabor filters. As a product of this operation, phasors (complex coefficients) are computed. In order to obtain iris signature, phasors are evaluated and coded by their location in the complex plane. However the Daugman's method is patented which blocks its further development.

In another approach suggested, by Lye Wil Liam and Ali Chekima in their paper [4], the iris image is pre processed for contrast enhancement. After preprocessing, a ring mask is created and moved through the entire image to obtain the iris data. By using this data the iris and pupil are reconstructed from the original picture. Using the iris center coordinate and radius, the iris was cropped out from the reconstructed image. The iris data (iris donut shape) is transformed into a rectangular shape. Using a self- organized feature map the iris pattern is matched. The network contains a single layer of Euclidean weight function. Manhattan Distances are used to calculate the distance from a particular neuron X to the neuron Y in this neighborhood. The Manhattan Distances without a bias and a competitive transfer function is used to upgrade the weight.

Bradford Bonney, Robert Ives in their paper [5] suggested a new approach for iris localization. They suggest morphological operations for extraction of the iris from the original image. They used Dilation and Erosion operation for this process. To isolate the limbic boundary from the pupil boundary, the authors used standard deviation windows in the vertical and horizontal directions. The resulting standard deviation windows are thersholded in order to produce a binary image. By erosion and dilation operations, these standard deviation windows a single row or column vector is obtained. To determine the location of the limbic (iris) boundary, these vectors are used. Once the boundary of limbic are is determined using (4) the elliptical curve is fitted. The resulting area between the pupillary boundary and limbic boundary forms the mask. The purpose of this method is to extract iris information of non-orthogonally captured iris images. They suggested that with some additional modifications to the limbic boundary detection, this approach is applicable to non-orthogonal iris images also.

Lu Chenghong and Lu Zhao yang [6] followed a different procedure for iris recognition. They have used Laplacian of Gaussian (LoG) filters for extracting and encoding the blob features extracted from the images. The iris code can be constructed using a binary sequence according to the final blob detection results.

In another method followed by Jie Wang [7] the iris texture extraction is performed by applying wavelet packet transform (WPT) using Haar wavelet. The iris image is decomposed in to sub images by applying WPT and suitable sub images are selected and WPT coefficients are encoded.

K.Grabowski and W.Sankowski have designed another method for iris features extraction method. In their paper [8], Haar wavelet based DWT transform is used.

The content of this paper is organized as follows. Section II describes the details of Morlet based approach and Statistical model based approach. Section III presents the results of applying Morlet approach and statistical model based approach on the iris database UBIRIS. Finally, conclusions and perspectives are given in section IV.

## 2. Iris Recognition System

An iris recognition system can be decomposed into three modules: an iris detector for detection and location of iris image, a feature extractor to extract the features and a pattern matching module. The iris is to be extracted from the acquired image of the whole eye. Therefore, before performing iris pattern matching, the iris is to be localized and extracted from the acquired image.

### *A. Iris Localization*

The first step is iris localization. Using the Integrao Differential Operator (IDO) (1) the iris is localized.

$$\max_{(r,x0,y0)} \left| G_\sigma * \frac{\partial}{\partial r} \oint_{r,x0,y0} \left( \frac{I(x,y)}{2\pi r} \right) ds \right| \quad \text{-- (1)}$$

where $I(x, y)$ is a raw input image. The IDO (1) suggested by J.Daughman [1][2] searches over the image domain $(x, y)$ for the maximum in the blurred partial derivative with respect to increasing radius $r$, of the normalized contour integral of $I(x, y)$ along a circular arc $ds$ of radius $r$ and center coordinates $(x0, y0)$. The symbol $*$ denotes convolution and $G_\sigma(r)$ is a smoothing function such as a Gaussian of scale $\sigma$. This operator actually behaves as a circular edge detector, blurred at a scale $\sigma$. It searches iteratively for the maximal contour integral derivative at successively finer scales of analysis through the three-parameter space $(x0, y0, r)$ defining a path of contour integration. It finds both pupillary boundary and the outer boundary of the iris. The results are shown in figures 1,2,3 and 4.

***Fig 1-Iris Image1***

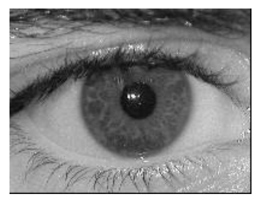

***Fig 2-Iris Image 2***

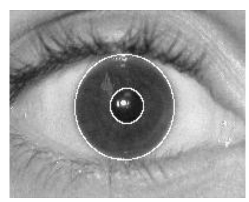

***Fig 3- Iris Localization of Iris Image 1***

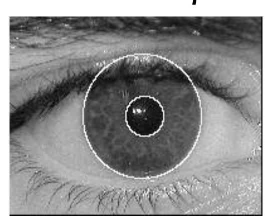

***Fig4- Iris Localization of Iris Image 2***

### *B. Iris Normalization*

After the iris is localized the next step is normalization (iris enrollment). Using the equations (2) the iris data are extracted. Different circles with increasing radius and angle are drawn starting from the pupil centre till it reaches near the iris coordinates. The information is extracted.

$$x = c(x) - r * \sin(\theta)$$
$$y = c(y) + r * \cos(\theta) \qquad \text{------ (2)}$$

where $c(x, y)$ denotes center coordinates, $(x, y)$ denotes coordinates of the image, $\theta$ is the angle and $r$ denotes the radius. Figure 5 shows the extracted (normalized) iris data.

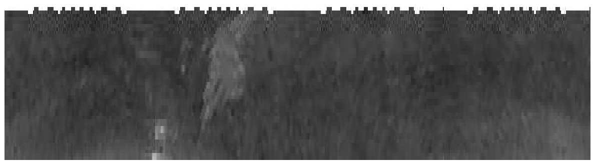

***Fig 5 - Normalized Iris Data***
***(Extracted Iris Data of Fig 1)***

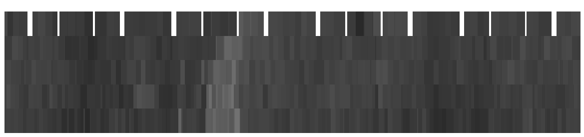

***Fig 6 - Normalized Iris Data***
***(Extracted Iris Data of Fig2***

*C. Iris Feature Extraction*
*(Morlet Wavelet Approach)*

The next step is extracting features from the normalized iris data. In our approach we used Morlet wavelet for feature extraction. Morlet wavelet is the arguably original wavelet. The Morlet wavelet is a locally periodic wave train. It is obtained by taking a complex sine wave and by localizing it with a Gaussian (bell-shaped) envelope. One- dimensional (1D) Morlet wavelet is shown in figure 7.

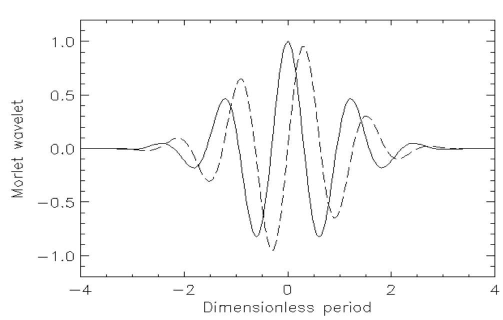


***Fig 7 - Plot of 1d Morlet Wavelet***

The Morlet wavelet transform will have a real and an imaginary part, and it is useful to represent them in `polar' coordinates: the norm is the magnitude of the transform and, being related to the local energy, is of primary interest, while the polar angle (phase) completes the representation. We have chosen the Morlet wavelet because it is directional (in the sense of being effective in selecting orientations) and capable of fine tuning specific frequencies [9]. This latter capability is especially important in filtering out the background noise of the images. These characteristics of the Morlet wavelet represent its advantages with respect to other standard filters such as the Gaussian and its derivatives.

Morlet wavelets are naturally robust against shifting a feature in time. Little or no special precautions are needed to ensure that a feature will make itself known in the same way no matter when it occurs. Morlet wavelet achieves the bound imposed by the Heisenberg Uncertainty Principle.

Though Gabor wavelet exactly meets the Heisenberg principle, it is computationally difficult to implement. Moreover design of Morlet wavelet filter banks is easy in the image processing applications. Hence in place of Gabor wavelet, Morlet wavelet can be used. The Morlet wavelet is approximately orthogonal, but not exactly. Due to the extended tails of the Gaussian, it is not possible to construct a truly orthogonal set for the Morlet.
The 2-D Morlet wavelet is defined as shown in (3)

$$\psi(x, y) = \exp(j(k_0 x + k_1 y)).\exp(-0.5\,|\,Ax|^2 + y^2) \; (3)$$

In (3) which is actually a complex exponential multiplied by 2 D Gaussian $j = \sqrt{(-1)}$, $A$ = diag [ $\xi$ -1/2, l], $\xi$ >=1, $k_0$ and $k_1$ are scalars that define the frequency of the complex exponential. Using the 2-D Morlet wavelet the phase information is extracted from the iris image. The values used are $k_0$ =0.8, $k_1$ =0.4, $\xi$ =2, and $A$ =10. The plot of the two dimensional (2D) Morlet wavelet is shown in figure 8.

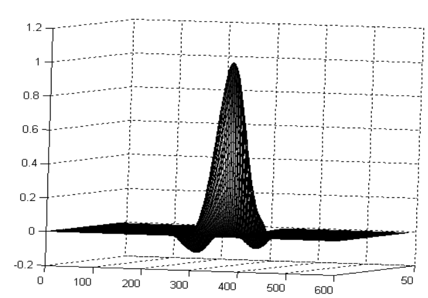


***Fig 8 - Plot of 2d Morlet Wavelet***

*D. Iris Feature Encoding and Matching*

The extracted phase information is encoded using gray scale code [1]. In rotating between any adjacent phase quadrants, only a single bit changes, unlike a binary code in which two bits may change, making some errors arbitrarily more costly than others. Altogether, 2025 such phase bits are computed for each iris. Only phase information is used for recognizing irises because amplitude information is not very discriminating, and it depends upon extraneous factors such as imaging contrast, illumination, and camera gain. The phase bit settings [1], which code the sequence of projection quadrants, are shown below in Table 1.

***Table 1 Phase Bit Settings***

| **Angle (in degrees)** | **Phase bits** |
|---|---|
| 0-90 | 11 |
| 91-180 | 1 |
| 181-270 | 0 |
| 271-360 | 10 |

In this method iris codes are constructed. Depending on the value of the phasor information (the quadrant in which it lies), the feature vectors are encoded. Two bits are assigned for each vector as given in Table 1 for matching the iris codes modified Hamming Distance HD as shown in (4) is used.

$$HD = \frac{codeA \otimes codeB}{n} \text{ ----- (4)}$$

In (4) $codeA$ and $codeB$ are iris codes of 2 iris to be compared, $\otimes$ denotes bit wise exclusive OR operation and $n$ is number of bits in code A.

E. *Wavelet Packet Transform (WPT) approach*

Wavelet Packets Transform (WPT) is a generalization of Wavelet Transform that offers a richer signal analysis. With WPT, it is possible to zoom into any desired frequency channels for further decomposition. Compared with WT, WPT offers a finer decomposition. When processing some oscillating signals, partition of low frequency parts is not fine enough. WPT can overcome this problem via decomposing high frequency components and more details obtained in WPT yield better representation of signals. As a progressive texture classification algorithm, WPT gives reasonably better performance because the dominant frequencies of iris texture are located in the low and middle frequency channels.

Iris texture extraction with WPT and encoding procedure involves three steps:

1. *Decomposition*. At each stage in the decomposition part of a 2-D WPT, four output sub images are generated. The images contain approximation (A), horizontal detail (H), vertical detail (V) and diagonal detail (D) coefficients respectively. After 3-level WPT, an image has a quad tree with 64 output sub images, each representing different frequency channels.

2. *Selection of candidates sub-images for feature encoding*. Processing wavelet coefficients of every sub image is a fair amount of work; furthermore, some of them are representations of high frequency noise, which reduce our ability to distinguish each iris. It is advisable to choose a subset of all possible sub images to make our encode process. The useful sub images with entropy criterion to make our analysis much more efficient and just as accurate using (5).

$$Entropy = -\sum_i \sum_j S_{i,j}^2 \log(S_{i,j}^2) \quad (5)$$

In (5) $S_{i,j}$ is the coefficient of the sub image. It is found that sub-image 10 retains higher entropy than other sub images. Hence it is chosen as the candidate sub-image for feature extraction.

A code matrix can be achieved by quantizing the coefficients into one data element each with a suitable threshold T as shown in (6)

$$C_{ij} = 1 \text{ if } S_{ij} > T \text{ ; } C_{ij} = 0 \text{ , } |S_{ij}| < T \text{ ; } C_{ij} = -1, S_{ij} < \text{-T;} \quad (6)$$

where $S_{ij}$ is the coefficient of a sub-image, $C_{ij}$ is the corresponding code element and $T$ is Threshold is a positive number. Equation (6) has 2 abilities of de-noising and finding singular points. $T$ is chosen as

***Table 2 Hamming Distance for Different Iris Images***

| **Iris Image Class** | **FAR** | **FRR** |
|---|---|---|
| 106 | 0 | 0.1 |
| 107 | 0 | 0.1 |
| 108 | 0.1 | 0.1 |
| 109 | 0.2 | 0.1 |
| 110 | 0.1 | 0.1 |
| 112 | 0.1 | 0.2 |

$T = 3\sigma$ and $\sigma$ is the variance of the noise. It is reported that the Standard Deviation of the WPT high frequency coefficients (sub -image 84) are having the good estimation of $\sigma$. The code matrix gives a good description of both frequency and location content of an image.

***Table 3 Hamming distance for Different Iris Images of Same Class (Image 85)***

| Iris Image Class | FAR | FRR |
|---|---|---|
| 106 | 0.0 | 0.125 |
| 107 | 0.0 | 0.125 |
| 108 | 0.125 | 0.125 |
| 109 | 0.375 | 0.125 |
| 110 | 0.10 | 0.25 |
| 112 | 0.10 | 0.25 |

***Table 4 Far and Frr Values Using Symlets Order 4***

| Iris Image Class | FAR | FRR |
|---|---|---|
| 106 | 0.0 | 0.125 |
| 107 | 0.0 | 0.125 |
| 108 | 0.0 | 0.0 |
| 109 | 0.30 | 0.25 |
| 110 | 0.125 | 0.25 |
| 112 | 0.125 | 0.25 |

In this proposed approach, Symlets wavelets are used for extracting the iris texture extraction. Symlets of order 4, order 6, order 8 are used to extract the iris texture information.

From UBIRIS database, 5 different iris images of 30 persons are taken (150 samples of iris) and code matrix are formed. When a new iris image is presented as an input, the code matrix of the image is found out. Using the modified hamming distance, the pattern matching is performed. Based on this value, the class to which the new image belongs to is calculated. With this information the False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) for each class are calculated for testing images.

## 3. Results

By applying the above stated Morlet based approach for iris images 85, 76, 95 and 107, the results obtained are shown below in Table 2. In this iris codes of above images are compared with iris code of image 22.

***Table 5 Far and Frr Values Using Symlets Order 6***

| Iris Image | Modified Hamming Distance |
|---|---|
| 76 | 0.044444 |
| 85 | 0.029136 |
| 95 | 0.041481 |
| 107_1 | 0.030123 |
| 107_2 | 0.030667 |

***Table 6 Far and Frr Values Using Symlets Order 8***

| Iris Image | Modified Hamming Distance |
|---|---|
| 85_1 | 0.006914 |
| 85_2 | 0.009877 |
| 85_4 | 0.008889 |

Using WPT method, the code matrix for the new iris images is computed. For iris images of class 106, 107,108 and 109, FAR and FRR are calculated. The computed False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) using Symlets of order 4 are as shown in Table 4. Using Symlets of order 6 and order 8 False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) are calculated. They are shown in Table 5 and Table 6.

## 4. Conclusion and Future Work

The presented Morlet based approach and Wavelet Packet Tree based approach have been tested on the University of Bio Informatica (UBIRIS) database and better results are obtained. The proposed method has the advantage of computational ease while comparing with other methods. The feature of the proposed system is less computational complexity. If algorithms for detection and removal of eyelashes and eyelids are implemented, then accuracy could be improved. In the future we plan to implement the presented method or part of it into FPGA chip.

**References**


1. John Daughman “Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression”, IEEE Transactions on Acoustics, Speech and signal Processing, VOL.36, No.7, July 1988.
2. John Daughman, “High confidence visual recognition of persons by a test of statistical independence”, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, VOL.15, No.11, November 1993.
3. John Daughman, “How iris recognition works” *IEEE Transactions on Circuits and Systems for Video Technology*, VOL.14, No.1, January 2004.
4. Lye Wil Liam, Ali Chekima, Liau Chung Fan, “Iris recognition using self-organizing neural network”, *IEEE* 2002.
5. Bradford Bonney, Robert Ives, Delores Etter, “Iris pattern extraction using bit planes and standard deviations”, *IEEE* 2004.
6. Lu Chenghong, Lu Zhao yang, “Efficient iris recognition by computing discriminable textons”, *IEEE* 2005.
7. Jie Wang, Xie Mei, “Iris Feature extraction based on wavelet packet analysis”, *IEEE* 2006.
8. K.Grabowski, W.Sankowski,”Iris recognition algorithm optimized for hardware implementation”, *IEEE* 2006.
9. Jorge Leandro, Roberto M Cesar, “Blood vessel segmentation in Retina”, *IEEE* 2001.
10. Gonzalez and woods, “Digital image processing”, 2nd edition .Addison wisely.
11. UBIRIS database : http://www.di.ubi.pt/~hugomcp.com