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Design and Analysis of Pattern Recognition System Based on Sclera Using Machine Learning Algorithms

S.Hariprasath[1], M.Santhi[2], T.N.Prabakar[3]
[1]Assistant Professor, Department of ECE , Saranathan College of Engineering, Panchappur, Trichy
E-mail:*hariprasath-ece@saranathan.ac.in*
[2] Professor, Department of ECE , Saranathan College of Engineering, Panchappur, Trichy
E-mail: *santhim@saranathan.ac.in*
[3]Professor, Department of ECE,Sri Sairam College of Enginee ring, Anegal, Bengaluru
E-mail: tnprabakar@gmail.com

Abstract

A Sclera recognition system based on Wavelet Packet Analysis is described in this paper. The intricate texture of each eye's iris is the most distinctive phenotypic characteristic apparent on a person's face. The apparent texture of a person's Sclera is encoded as a compact sequence of 2-D wavelet packet coefficients that produce a "Sclera code". Two different Sclera codes are compared using exclusively OR comparisons. In this study, we offer a novel multi-resolution technique based on Wavelet Packet Transform (WPT) for analyzing and recognizing the texture of the sclera. This method was inspired by the discovery that the predominant frequencies of the sclera texture are situated in the low- and middle-frequency channels. As a Sclera signature, WPT sub-image coefficients are quantified as 1, 0 or -1 using an adaptive threshold. This signature provides the regional details of several Sclera. By utilizing wavelet packets, the coding size of the Sclera signature is 640 bits. After calculating the signature of the new Sclera pattern, it is compared to the pattern that was previously saved. Identification is achieved by putting the test sclera code into a Multi-Layer Feed Forward Neural Network (MLFNN), which produces the identification result.

Keywords
Biometrics, Sclera pattern, Biorthogonal wavelet packets, Symlets, Wavelet Packet Transform, Multi-Layer Feed Forward Neural Network

I.INTRODUCTION

The word Sclera is generally used to denote the white portion of the eye. It is the portion of the eye structure excluding the complex structure called iris.. The image of a human Sclera thus constitutes a plausible biometric signature for establishing or confirming personal identity. Its inherent protection and isolation from the physical environment, and it's easily monitored physiological response to light. Additional technical advantages over other modalities for automatic recognition systems include the ease of registering the Sclera optically without physical contact beside the fact that its intrinsic polar geometry does make the process of feature extraction easier.

II. EXISTING METHODS

The first successful implementation of Iris recognition system was proposed by J.Daughman in 1993[3]. This work though published more than 25 years ago still remains valuable 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 of the convolution of image with complex Gabor filters. As a product of this operation, phasors (complex coefficients) are computed. 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. 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 Sclera 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 neuron Y in this neighborhood. The Manhattan Distances without a bias and a competitive transfer function are used to upgrade the weight.

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 into sub-images by applying WPT and suitable sub-images are selected and WPT coefficients are encoded.

K.Grabowski and W. Sankowskiki 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 III describes the steps involved in Sclera Recognition System. Section IV presents our proposed approach using Wavelet packets based approach. Section V gives the results of Wavelet packet Transform-based direction on the Sclera database UBIRIS. Finally, conclusions and perspectives are given in section VI.

III. SCLERA RECOGNITION SYSTEM

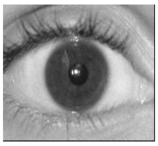
A Sclera recognition system can be decomposed into three modules: a Sclera detector for detection and location of Sclera image, a feature extractor to extract the features and a pattern matching module for matching. The Sclera is removed from the acquired image of the whole eye. Therefore, before performing Sclera pattern matching, the Sclera must be localized and extracted from the acquired image. The procedure adopted in this work is that after the iris texture is extracted, it is saved as a texture image. The saved texture image is subtracted from the original eye image. The output is an image comprising blood vessel information present in the sclera part of the eye.

A. iris Localization

The first step is iris localization. The iris is localized using the Integro Differential Operator (IDO) (1) iris is localized.

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

where $I(x, y)$ is a raw input image. The IDO (1) suggested by J.Daughman [1][2] searches over the image main (x, y) for the maximum in the blurred partial derivative concerning to an increasing rad r , of the normalized contour integral $I(x, y)$ 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 σ . This operator acts as a circular edge detector, blurred at a scale σ . 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 p h of contour integration. It finds both pupillary boundary and the outer boundary of the Sclera. The results are shown in figures 1 and 2.



Fig,1 eye Image1

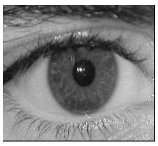


Fig.2 eye Image2

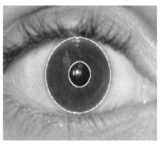


Fig.3 iris localization of iris in Image1

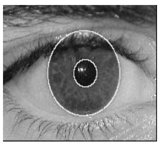


Fig.4 localization of iris in Image2

B. Iris Normalization

After the Iris is localized the next step I,s normalization (Sclera enrollment). Using the equations (he Iequationare e,xtracted. Different circles with increasing radius and angle are drawn starting from the pupil centre till it reaccenterar the Sclera coordinates. The information is extracted.

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

where $c(x, y)$ denotes center co dinates, (x, y) denotes coordinates of the image, θ is the angle and r denotes the rad,ius. Figure 3 shows the extracted (normalized) Sclera data.

Fig 5- Normalized iris Data (Extracted iris Data) Of Fig 1

Fig 6- Normalized iris Data (Extracted iris Data) Of Fig 2

C. Wavelet Packet Transform (WPT) approach

The standard discrete wavelet transform (DWT) is a very powerful tool used successfully to solve various problems in signal and image processing. The DWT breaks an image down into four sub-sampled images. The results consist of one image that has been high passed in the horizontal and vertical directions (HH), one that has been low passed in the vertical and high passed in the horizontal (LH), one that has been high passed in the vertical and low passed in the horizontal (HL) and last that has been low pass filtered in both directions (LL) Where, H and L mean the high pass and low pass filter, respectively. While HH means that the high pass filter is applied to signals of both directions, represent diagonal features of the image, HL correspond to horizontal structures, LH correspond to vertical information and LL is used for further processing.

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. It is shown in Figure 7.

2. *Selection of candidates sub-images for feature encoding.*

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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 (3).

$$Entropy = -\sum_i \sum_j S_{i,j}^2 \log(S_{i,j}^2) \quad (3)$$

In (3) $S_{i,j}$ 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.

3. Sclera Feature Encoding

A code matrix can be achieved by quantizing the coefficients of candidate sub-image and LL3, HL3 or LH3 into one data element each with a suitable threshold T as shown in (6)

$$C_{ij} = 1 \text{ if } S_{ij} > T \text{ ; } C_{ij} = 0 \text{ , } | S_{ij} | < T \text{ ; } C_{ij} = -1 \text{ , } S_{ij} < -T; \quad (4)$$

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 (4) has 2 abilities of de-noising and finding singular points. T is chosen as $T = 3\sigma$ and σ 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 σ. The code matrix gives a good description of both frequency and location content of an image. The chosen sub image is called candidate sub-image.

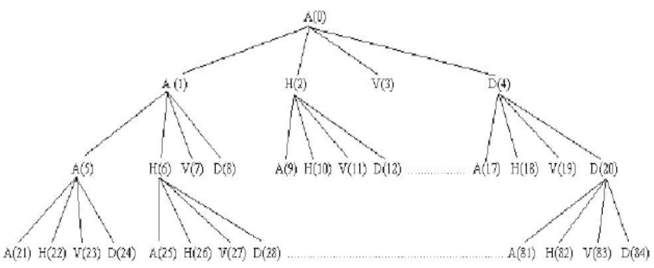

Fig.7-Wavelet Packet Tree Decomposition

D. Sclera Matching

For matching the Sclera codes, MLFNN is used. In the proposed Multi-Layer Feedforward Neural Network, three layers are designed. The MLFNN has eight neurons in the input layer, four neurons in the middle layer, and two neurons in the output layer.

IV. OUR PROPOSED METHOD

In this particular approach, the Sclera images are encoded using wavelet packets to formulate a template. Instead of traditional multi-resolution analysis, a novel lifting technique is used to construct the biorthogonal filters [10]

The main advantage of this scheme over the classical construction is that it does not rely on the Fourier transform. Also, it allows faster implementation of the wavelet transform. The basic idea behind the lifting scheme is shown in Fig.8. It starts with a trivial wavelet, the ``Lazy wavelet"; which has the formal properties of the wavelet but is not capable of doing the analysis.

The lifting scheme then gradually builds a new wavelet, with improved properties with improved properties by adding a lifting scheme to be visualized as an extension of the FIR (Finite Impulse Response) schemes [10]

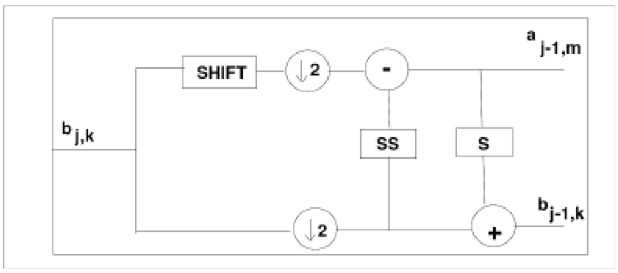

Fig.8-The Lifting Scheme for Wavelets

It first calculates the Lazy wavelet transform, then calculates the $a_{i-1,m}$ and finally lifts the b_{j-1-k}. It is known that any two-channel FIR sub band transform can be factored into a finite sequence of lifting steps. Thus, implementation of these lifting steps is faster and efficient. The biorthogonal filter family is shown in Fig. 9. The frequency content of the resulting coefficients is adjusted each time to get separated band structure.

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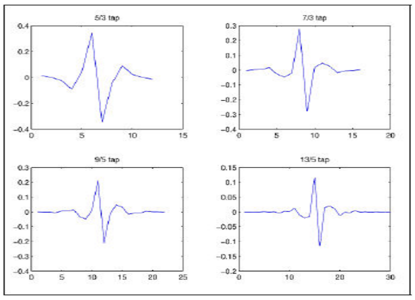

Fig.9- Biorthogonal Filter Family

In this work we have used Symlets and Coiflets as mother wavelets. We have decomposed the normalized image up-to third level of decomposition. In order to create the feature vector we tried different combinations of LH3, HL3, and HH3 with candidate sub-image. The results obtained from different combinations are compared to find the best. The binary feature vector that is generated by quantizing the feature vector obtained by the combination of LH3, HH3 with the candidate sub-image is found suitable for encoding in our work.

V. RESULTS

From UBIRIS database, 8 different iris images of 30 persons are taken (240 samples of iris) and code matrix is formed. When a new Sclera image is presented as an input, the code matrix of the image is found out. Using the MLFNN, 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.

The calculated False Acceptance Ratio (FAR) and False Rejection Ratio (FRR) using Symlets of order 6 and order 8 are shown in Table 1 and Table 2. FAR and FRR values using Coiflets wavelets of order 2 and 3 are shown in Table 4 and Table 5.

Table.1 FAR and FRR Values Using Symlets Order 6

Sclera Image Class	FAR	FRR
106	0.0	0.125
107	0.0	0.125
108	0.25	0.0
110	0.25	0.25
112	0.25	0.40

Table.2 FAR and FRR values using Symlets order 8

Sclera Image Class	FAR	FRR
106	0.0	0.125
107	0.0	0.125
108	0.250	0.125
110	0.25	0.250
112	0.25	0.40

Table.3 FAR and FRR Values Using Coiflets Order 2

Sclera Image Class	FAR	FRR
106	0.0	0.125
107	0.0	0.125
108	0.250	0.125
110	0.25	0.250
112	0.25	0.40

Table.4 FAR and FRR Values Using Coiflets Order 3

Sclera Image Class	FAR	FRR
106	0.0	0.125
107	0.0	0.125
108	0.0	0.125
110	0.0	0.25
112	0.0	0.25

Table.5 accuracy in terms of feature vector length for different wavelets

Wavelet	Accuracy %	Feature Vector Length
Sym2	81.50	288
Sym3	90.50	480
Sym4	89	460
Sym6	93	960
Sym8	88	960
Coif2	86	640
Coif3	87	720
Coif4	90	720

The Performance of the proposed Sclera recognition system using Symlets wavelets is shown in figure 10. In figure 10, classes refer to the image classes of Sclera images. Class 1 refers to user 106, and class 8 refers to user 113.

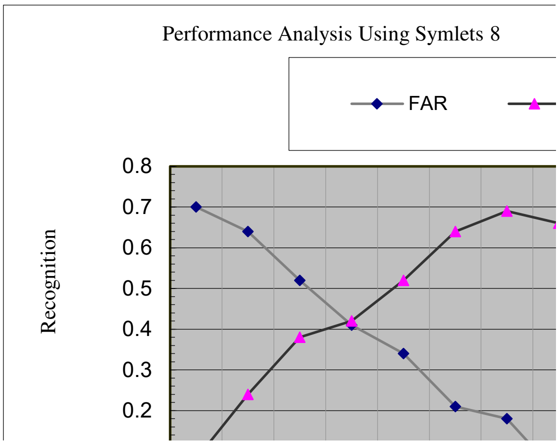

Fig.10 Performance analysis of Symlets wavelet packets

Figure 11 and figure 12 shows the performance curve of the proposed system using Coiflets wavelets. In figure 11 and 12, classes refer to the image classes of Sclera images. Class 1 refers to the user 106 and class 8 refers to user 113.

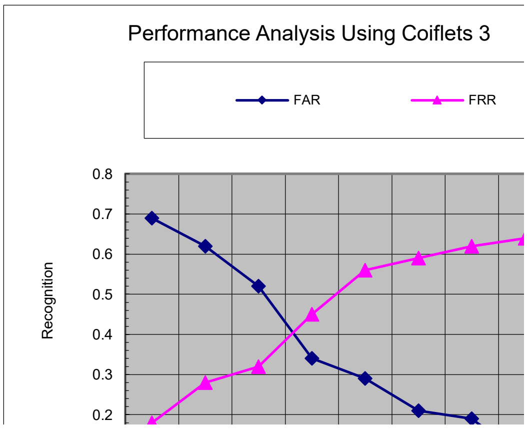

Fig. 11 Performance analysis of Coiflets wavelet packets

From the figures 10 and 11 it can be seen that the EER value of recognition system decreases as the mother wavelet chosen is varied. For Symlets wavelets the EER value is 0.41 whereas for Coiflets it is 0.34.

The accuracy of the proposed system varies when different feature vector is chosen. The performance curve of the system in term of accuracy for feature vector using various mother wavelets are is shown in figure 13.

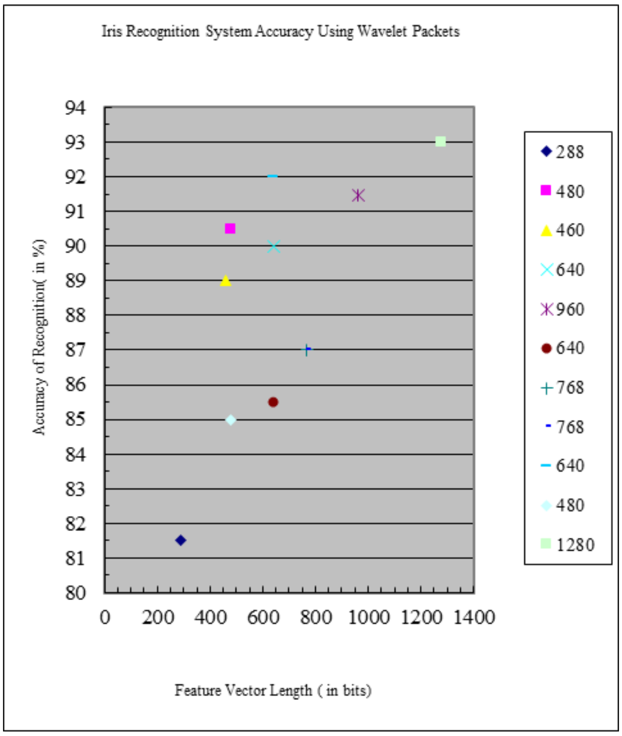

Fig.12 Sclera Recognition system accuracy in terms of Feature vector length

V. CONCLUSION

The experimental results clearly demonstrate that the feature vector consisting of concatenating the candidate sub-image, LH3 and HH3 gives better results. On the other hand, the Symlets wavelet is particularly suitable for implementing high-accuracy Sclera verification /identification systems, as feature vector length is at the least compared to other wavelets. The Coiflets wavelets gives better EER performance compared to other wavelet packets. But the feature vector size is little high compared to biorthogonal wavelets. For a reduction of 3% accuracy, the length of the feature vector and no of bits required to represent the Sclera signature is reduced substantially in the case of coiflets wavelets. If algorithms for the detection and removal of eyelashes and eyelids are implemented, then accuracy could be improved.

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