VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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A PIPELINED APPROACH FOR FPGA IMPLEMENTATION OF BI MODAL BIOMETRIC PATTERN RECOGNITION

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ABSTRACT

A Biometric system is essentially a pattern recognition system that makes use of biometric traits to recognize individuals. Systems which are built upon multiple sources of information for establishing identity which are known as multimodal biometric systems can overcome some of the limitations like noisy captured data, intra class variations etc… In this paper a Bi modal biometric system of iris and palm print based on Wavelet Packet Transform (WPT), gabor filters and a neural classifier implemented in FPGA is described. Iris is the unique observable visible feature present in the detailed texture of each eye. Palmprint is referred to the textural data like principal lines wrinkles and ridges present in the palm. The visible texture of a person's iris and palm print is encoded into a compact sequence of 2-D wavelet packet coefficients constituting a biometric signature or a feature vector code. In this paper, a novel multi-resolution approach based on WPT for recognition of iris and palmprint is proposed. With an adaptive threshold, WPT sub image coefficients are quantized into 1, 0 or -1 as biometric signature resulting in the size of biometric signature as 960 bits. The combined pattern vector of palm print features and iris features are formed using fusion at feature level and applied to the pattern classifier. The Learning Vector Quantization neural network is used as pattern classifier and a recognition rate of 97.22% is obtained. A part of the neural network is implemented for input data of 16 dimensions and 12 input classes and 8 output classes, using virtex-4 xc4vlx15 device. This system can complete recognition in 3.25 microseconds thus enabling it being suitable for real time pattern recognition tasks.

Keywords: feature level fusion, bimodal biometric system, FPGA implementation, LVQ neural network.

1. INTRODUCTION

Biometric authentication is the process of establishing a human identity based on a person's physical or behavioral traits. An automated biometric authentication system compares the feature set extracted from the input raw data applied to it as input with the identity models stored in the database. The entire process is performed either to verify a claimed identity or to determine the individual's identity. The performance of such system is evaluated by measuring the trade-off between the false accept rate (FAR) and the false reject rate (FRR). For any system, it is not possible to reduce these two error rates simultaneously. By building a system which accepts more than one biometric trait these two error rates can be reduced considerably. Most multi biometric systems described in the literature employ a common fusion mechanism for all users. Such multibiometric systems [1], merge the information presented by multiple sub-systems. When N independently constructed sub-systems function together, the N output scores are to be consolidated into a single output. This is the problem of score-level fusion which is the most popular fusion approach due to the ease of accessing scores from commercial matchers. In this paper we have followed feature level fusion. The feature vectors are extracted by computing texture features from iris and palm print with the help of gray level co-occurrence matrix and combined to form a single pattern vector.

The computational power requirement of pattern recognition systems are not achieved by embedded systems built with microprocessors. One solution to the problem is the hardware implementation of software algorithms using Field Programmable Gate Arrays (FPGAs). FPGAs allow the customization of both the architecture and the functionalities of the system for a given purpose. The concurrent design and operation is one of the outstanding features of such reconfigurable devices. Due to its availability and performance, FPGAs have been used in powerful reconfigurable systems. Therefore, systems based on reconfigurable hardware can offer custom-computing machines for specific applications, with orders of magnitude faster than regular software processing in general-purpose processors [2].

The objective of this work is to propose a methodology for the implementation of a Learning Vector Quantization (LVQ) Neural Network (NN) as classifier for pattern recognition of iris and palm print using a reconfigurable device. LVQ NNs are frequently used for pattern recognition problems ([3], [4]) and found to be suitable for hardware implementation. Since they are working based on geometric distance calculation between input samples and reference vectors they require less number of multipliers and less clock cycles.

2. EXISTING SYSTEMS

The first successful implementation of iris recognition system was proposed by J. Daughman in 1993[5]. This work though published more than 30 years

VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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ago still remains valuable since because it provides solutions for each part of the system. Most of the systems implemented today are based on this work. They are based on Gabor wavelet analysis [5] [6] [7] 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, 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 [8], 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.

In another method followed by Jie Wang [9] 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 [10], Haar wavelet based DWT transform is used.

Ajay Kumar and Helen C. Shen [11] proposed an approach in which Gabor filter is used for palm print recognition. Fang Li et al. [12] proposed an approach utilizing Line Edge Map (LEM) of palm print as the feature and Hausdorff distance as the distance matching algorithm.

The content of this paper is organized as follows. Section III describes the steps involved in multimodal biometric recognition System. Section IV presents biometric fusion method in general. Section V presents our proposed approach using WPT, LVQ classifier and hardware implementation. Section V gives the results of WPT based feature extraction approach on the iris and palm print database classified using LVQ and hardware implementation results. Finally, section VI gives conclusions and perspectives.

3. BIOMETRIC FUSION

Generally, most biometric systems employ only one biometric modality for identity management, i.e. only a single distinguished biometric source is utilized during the recognition process. As a result, unimodal biometric systems are intolerant of noise arising from distorted input data acquired by the sensor, signal distortion caused by environmental factors and changes of physical traits over time. In contrast, a multi-biometric system offers the following benefits [1]: (i) lower error rate – an amalgam of the information acquired from various sources could possibly reduce error rate, (ii) improved availability – if one biometric trait is missing, this can be supported by other available traits, (iii) higher degree of freedom – a multi-biometric system is able to recognize a user even if he or she uses only a subset of the employed biometrics, (iv) less susceptible to spoof attacks – spoofing of multiple traits at the same time is not easy, and (v) higher robustness

In general, a biometric system[1] comprises of four parts, namely, (i) sensor module – to acquire raw biometric impression(s), (ii) pre-processing and feature extraction module – to enhance the acquired impression(s), and to extract salient characteristics from them, (iii) matcher module – to compare the query features with the stored template in order to produce a match score, (iv) decision module – to authenticate or reject a user by comparing the match score against a predefined threshold. Fusion can use multiple representations of a single biometric, a single biometric with multiple matchers or multiple biometric identifiers. Fusion can be performed at different levels: sensor level, feature level, confidence level and abstract level. In this paper feature level fusion technique is used to combine the features extracted from iris and palm print data. Figure-1 shows the block diagram of multimodal biometric system using feature leave fusion. For computing the feature vector for combined multimodal system, individually the features are extracted using a feature extractor [1].

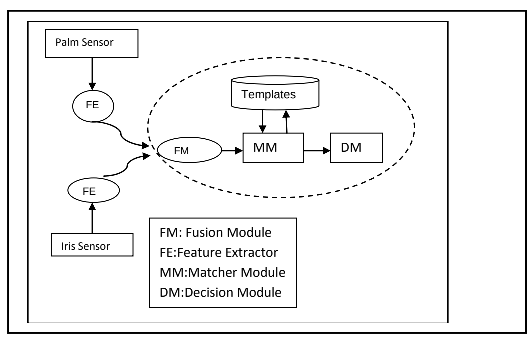

Figure-1. Multimodal biometric system using feature level fusion.

In our implementation we have used wavelet packet transform followed by GLCM Unit as Feature Extractor (FE) for iris pattern and Gabor filter for palm print pattern. The extracted image features are applied to GLCM calculator which computes the textural features. As both iris image and palm print are rich with textural information, the co occurrence matrix computed is also rich in features which adequately describe the biometric input. A set of 12 features from iris and a set of 6 features from palm print are computed. By concatenation of 8 features from iris and 4 best features from palm print, the feature set is reduced in size to produce a multi modal pattern vector of size 12 and applied to LVQ neural network. The pattern vector formation is completed using

VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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Matlab [13] tool and the resultant pattern vectors are stored in a text file from which the FPGA module of LVQ neural network reads the input vectors.

4. MULTI MODAL BIOMETRIC SYSTEM AND LVQ CLASSIFIER WITH HARDWARE IMPLEMENTATION

A. Multimodal Biometric System

In this particular approach, two different Feature Extractor modules are used. WPT is used for Iris data and Gabor filters are used for palm print data. The feature vectors are then combined into a multi modal pattern vector of dimension 12 and applied to LVQ classifier.

a) 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 for matching. 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.

i. Iris Localization

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

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

where $I(x,y)$ is a raw input image. The IDO (1) suggested by J.Daughman [5][6] 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 σ. This operator actually behaves 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 path of contour integration. It finds both pupillary boundary and the outer boundary of the iris. The results are shown in Figures-2 and 3.

ii. 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.

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

where $c(x,y)$ denotes center coordinates, (x,y) denotes coordinates of the image, θ is the angle and r denotes the radius. Figure-4 shows the extracted (normalized) iris data.

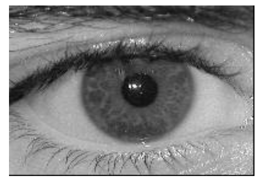

Figure-2. Iris image.

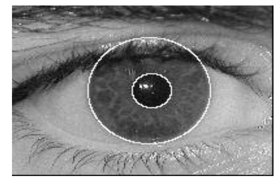

Figure-3. Localized iris image.

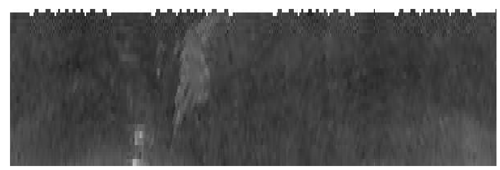

Figure-4. Normalized iris

iii. 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.

Biometric 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 [13].It is shown in Figure-5.

2. Selection of 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

VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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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).

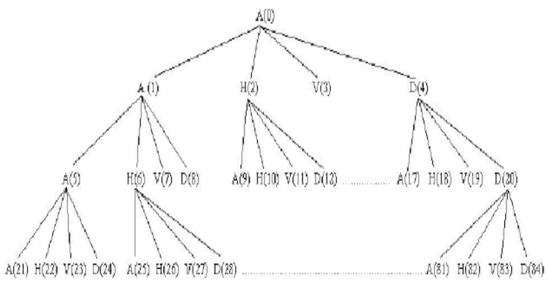

Figure-5. Wavelet Packet Decomposition [WPT].

$$Entropy = -\sum_{i}\sum_{j} S_{i,j}^{2} \log(S_{i,j}^{2}) \tag{3}$$

In equation (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.

b) Palm print Recognition System

Before feature extraction, it is necessary to obtain a sub-image from the captured palmprint image and to eliminate the variations caused by rotation and translation. After extracting the sub image as region of extraction by pre-processing, the texture features of the palm prints are extracted by Gabor filters decomposition scheme. The Gabor filter is an effective tool for texture analysis and has the following general form.

$$G(x, y, \mu, \omega, \theta) = \frac{1}{2\pi\sigma^{2}} \exp\left(\frac{-x^{2}+y^{2}}{2\sigma^{2}}\right) \exp(2\pi i)(\mu x \cos\theta + \mu y \sin\theta) \tag{4}$$

where i = -1, u is the frequency of the sinusoidal wave, ω controls the orientation of the function and σ is the standard deviation of the Gaussian envelope. The sample point in the filtered image as shown in Figure-6 is coded in to two bits (b_r, b_i) . Depending on the phase value of complex vector generated, using Table-1 phase bits are generated. Thus palm print code of 960 bits is generated.

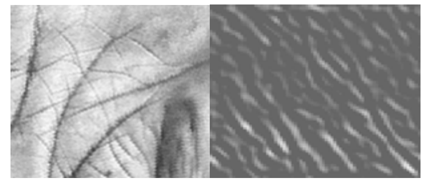

Figure-6. Preprocessed Palm Print and extracted features.

The GLCM calculations which are originally proposed by Haralick [14] are used to capture the texture information from transformed data. The best candidate sub image from WPT and gabor sub images are chosen and haralick features are computed. From the Haralick features computed for each biometric,8 iris features and 4 palm print features are combined to produce a pattern vector of dimension 18.The multi modal pattern vector which is of dimension 12 is used to train the LVQ classifier.

B. LVQ Neural Networks

The LVQ Neural Network (LVQ NN) is a method for training neural networks for pattern classification. In this method each output represents a particular class. Each class is referred by a weight vector which represents the center of the clusters defining the decision hypersurfaces of the classes. A given class can be defined by a single point or a set of classes, for a better representation of irregular decision surfaces. For training this NN it is necessary to have a set of training patterns with known classes and an initial distribution of the reference vectors. During training, each input sample x is taken along with its cluster center W (which is nearer to the input x). The known class T of input sample x and the class C represented by the cluster center w is compared. The center of the cluster w is updated according to equation 5, where α is the learning rate of the NN.

$$\begin{aligned} &if\ \ \mathrm{T= c}\ then\ \mathrm{w}_{new} = w_{prev} + \alpha.\left[x - w_{prev}\right] \\ &if\ \ \mathrm{T \neq c}\ then\ \mathrm{w}_{new} = w_{prev} - \alpha.\left[x - w_{prev}\right] \end{aligned} \tag{5}$$

Training is done for all input variables several times, always taken them in a random order. Usually, training is concluded when clusters get stable, or either a previously specified number of iterations is reached. Basically, after being trained, a LVQ NN becomes a vector comparator. Every new input will be assigned to a class which cluster center is the most similar to it. The similarity (or dissimilarity) measure of two generic points x and y can be implemented as the geometric distance between them. A general distance norm is given by equation 6, where n is the dimensionality of the space and wi a weighting coefficient.

By taking all the input variables in a random order training is performed several times and it is stopped when the clusters become stable or a previously set number of iterations is reached. After getting trained, a LVQ NN becomes a vector comparator. Whenvever a new input is presented to the nn, it is assigned to a class whose cluster

VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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centre is most similar to the input. The similarity (or dissimilarity) measure of two generic points x and y can be implemented as the geometric distance between them. By For certain applications which require faster computation, Manhattan distance which is shown in equation 6 is used as similarity measure.

$$d(x,y)=\sum_{i=1}^{n} w_i.\left|x_i-y_i\right| \tag{6}$$

C. Hardware implementation

The general implementation of neural networks in FPGA is reported in many works in the literature [15], [16]. In most of such works, the particular type of NN and its implementation is not discussed and instead general implementation is described. Better results can be achieved when the architecture particular to a specific NN is focused and implemented [16]. In our work, the implementation of LVQ NN for input pattern of dimension size 12 (pattern vector of 16 features are combined viz 8 features from iris data and 4 features from palm print data) and output class of size 3 are considered. The subclasses considered are 6 in size. From a pool of 60 iris and 60 palm print images (belonging to 12 iris class and 12 palm print class), 90 pattern vectors are used for training. The remaining 30 pattern vectors of dimension 12 are used for testing the trained NN.

A block of internal ROM memories used to store fixed LVQ weights for the K neurons (K=12). For each neuron j of the LVQ output layer, the Manhattan distance must be computed. The operator $|X_i - W_{ij}|$ is implemented by the architecture which is formed with a serial subtractor followed by serial on-line absolute value processor. The global architecture of the distance computation is given in figure 8. The small area of serial operators allows all the computations to be performed simultaneously by means of a column of M subtractors followed by a column of M absolute value processors. It provides M outputs that are connected to the M inputs of a simple tree of serial adders. The new Weights are calculated according to equation 7 and stored in the ROM. A comparator circuit is used to select minimal distance d_i according to the equation 1 and the corresponding winner neuron is selected. The winner neurons weights are updated using the equation 1.The overall architecture is shown in Figure-7 and classifier RTL diagram is shown in Figure-8.

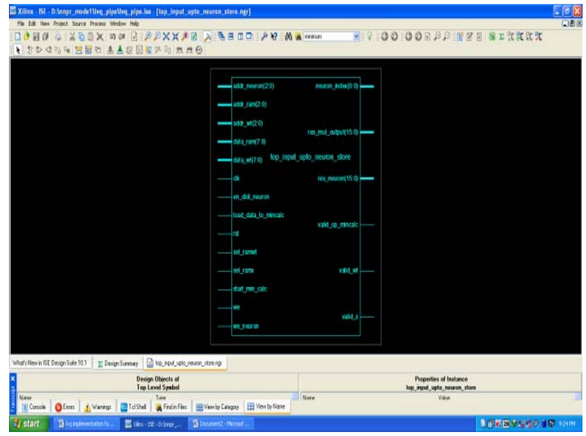

Figure-7. synthesis result of top block using Xilinx 10.1 tool.

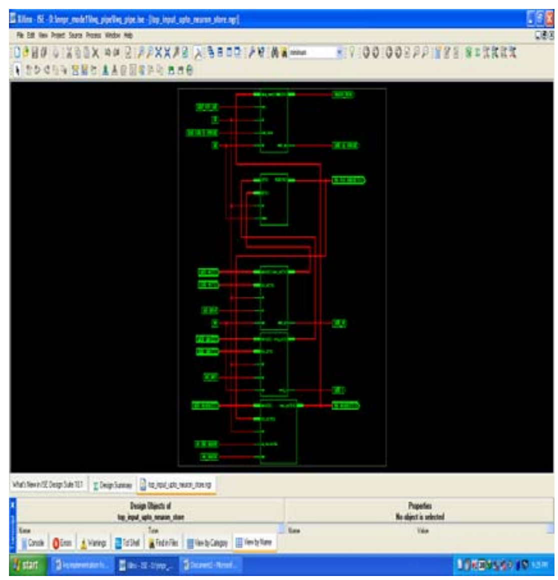

Figure-8. RTL block diagram of distance calculator used in LVQ neural network.

5. RESULTS AND DISCUSSIONS

The LVQ network architecture includes 12 units on the input layer, which represent the 12 classes formed by the concatenation of iris and palm print feature vectors. There are 3 units on the output layer that characterize the one of 9 output classes. After training with 75 % of the input data, testing is performed with the remaining data as described in section IV. The results of recognition in terms of False Acceptance Ratio and False Rejection Ratio are given in the table 1 for Iris and Table-2 for palm print and in Table-3 for combined recognition. The device utilization report is shown in Table-4.

VOL. 10, NO. 4, MARCH 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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Table-1. Recognition Performance of IRIS Feature Vector Using Difference Mother Wavelets.

Recognition performance		
Wavelet type	**Accuracy in %**	**Feature vector length**
Sym2	81.50	288
sym3	90.50	480
sym4	89.00	460
sym6	90.00	640
sym8	91.50	960
bior 1.5	92.00	640
bior 2.6	85.00	480
bior 3.9	93.00	1280

Table-2. Recognition performance of palm print feature vector.

Palm print recognition performance						
Threshold	0.8276	0.7589	0.6691	0.5646	0.7648	0.6399
FAR	89 %	73 %	40 %	14 %	76 %	31 %
FRR	6%	23 %	49 %	77 %	20 %	57 %

Table-3. Performance of Feature Vector For Multi Modal Biometric.

Modality	Accuracy in %	Feature vector length
Iris	91.50	960
Palmprint	89.46	960
Combination of Iris and Palmprint	97.22	960

Table-4. Device Utilization Report Summary for Virtex 4 Device.

Device utilization summary:

Selected Device : 4vlx15sf363-12
Number of Slices: 49 out of 6144 0%
Number of Slice Flip Flops: 64 out of 12288 0%
Number of 4 input LUTs: 64 out of 12288 0%
Number used as logic: 32
Number used as RAMs: 32
Number of IOs: 70
Number of bonded IOBs: 70 out of 240 29%
IOB Flip Flops: 2
Number of GCLKs: 1 out of 32 3%
Number of DSP48s: 1 out of 32 3%

The Performance of the proposed iris recognition system using bi orthogonal wavelets in WPT is shown in the Figure-9. In this figure classes refer to the image classes of iris images. Class 1 refers to the user 106 and class 8 refers to user 113. The accuracy of the proposed system varies when different feature vector is chosen.

The performance analysis of palm print recognition system using Gabor filters are shown in figure 10. By choosing the 3rd scale and 3rd orientation filtered image as candidate image for encoding, the FAR and FRR are calculated and EER obtained is 0.42%. This value is found to be high. To improve the EER value, further the palm print input image is filtered using other scales. When Gabor filter of scale 6 and orientation 3 is used, low EER rate obtained as 0.26%. It is shown in Figure-11.

By performing feature level fusion of the two feature vectors the accuracy of the recognition is increased. Table-3 shows that with same feature vector length, high accuracy can be achieved.

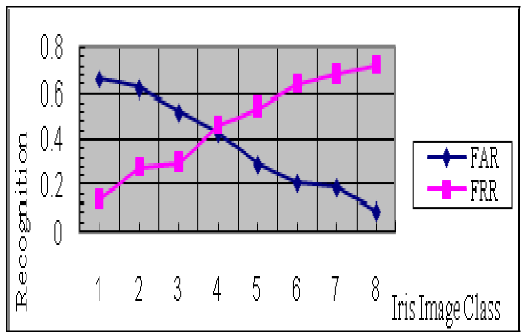

Figure-9. Iris recognition system performance using Bi orthogonal wavelets.

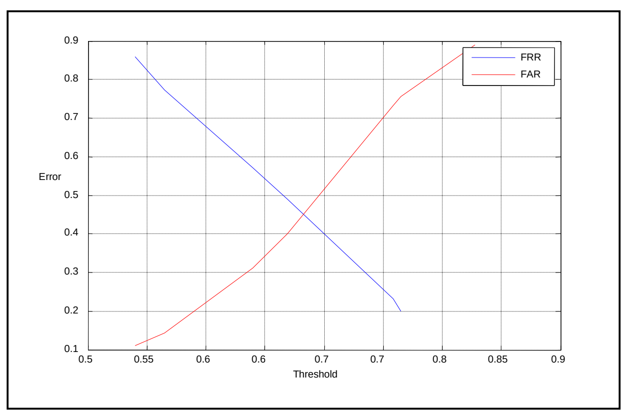

Figure-10. Performance analysis of Palmprint recogniton using Gabor filters.

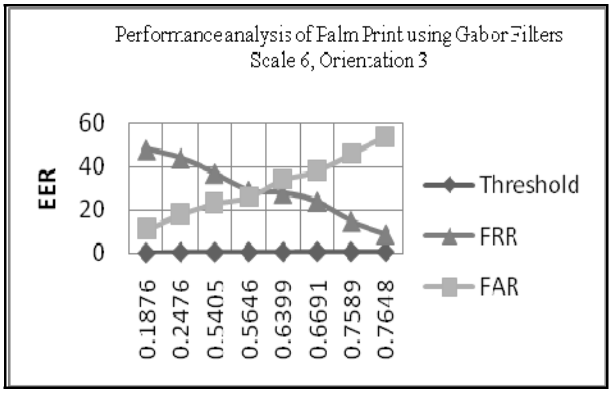

Figure-11. Performance analysis of palm print recognition using Gabor filters with scale 6, orientation 3

6. CONCLUSIONS

The experimental results clearly demonstrate that the feature vector consisting of concatenating the candidate sub-image, LH3 and HH3 (forming iris feature vector) and 3rd orientation of 6th scale decomposed palm print feature vector gives better results. By feature level fusion of palmprint and iris feature vectors, the overall recognition rate is improved. The Symlets wavelet is particularly suitable for implementing high-accuracy iris 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 iris signature is reduced substantially in the case of biorthogonal wavelets. The bior3.9 wavelet gives an accuracy of 93.00% but the feature vector length is approximately 5 times larger compared to feature vector obtained using Symlets wavelet By combining the iris and palm print recognition scheme the accuracy of the recognition is improved . The LVQ classifier which is implemented using virtex device gives a fast recognition in 3.25us which makes the system suitable for real time systems. By implementing all the modules of the LVQ network, a software and hardware combined model can be implemented in FPGA devices. With the available FPGA devices and optimization techniques, the operating frequency of the system can be increased.

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