Design, Analysis and Implementation of Multimodal Biometric Pattern Recognition System Using Multi Resolution Analysis in FPGA

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Abstract - The design of biometric pattern recognition with high accuracy, high robustness and good permanence is a significant design issue in pattern recognition system. An Authentication system in which recognition of authorised users are performed based on the physiological traits is called as biometric pattern recognition system.In general the unimodal biometric systems do not possessthe requisitefeatures like solidity, circumvention and permanence. When noisy data acquired from the sensor is given as input, the uni modal biometrics system's accuracy may reduce. The decrement in the system accuracy has many factors like the presence of noise in the recorded biometric input, the high variations of the feature of users belong to same class compared to the users belong to different class etc… Several such limitationscould beremoved by applying input data from multi biometric sources. In this work, the design of textural feature extractor and the distance based classifier for a bimodal biometric system in FPGA is described. The bimodal biometric system is created by feature level fusion of iris pattern vector and palmprint pattern vector. In iris pattern, using the gray level dependent matrix values obtained from wavelet packet decomposed sub-images, the features are extracted. Using gabor kernel, features are extracted from the palmprint pattern. By normalization followed by binarisation, the binary feature vector is created. Using Hamming Distance and its variant, the input biometric data are grouped into its constituent classes. The RTL description of the haralick feature vector and the modified Hamming Distance Classifier (MHDC) is written using VHDL 2008 language, and the design is implemented on Spartan 6 FPGA. With a speed grade of 4, the propagation delay of the critical path is 230.12 ns. The obtained delay is adequate for implementing the extractor and classifier as an off-chip design for real-time implementation.

Keywords: Biometric fusion, Bi modal biometric pattern recognition system, hamming distance classifier, modified hamming distance classifier, Manhattan classifier, iris recognition, Palmprint recognition

I. INTRODUCTION

The authentication of the users based on their characteristics is a scholarly task in the field of pattern recognition system. The characteristics used to recognize the users are of two types namely physiological features and actions made by them. The physiological features are unique for most of the time and remain as time invariant features. The features like iris, palm print, face, voice and keystroke are used in recognizing the legitimate users is it forms the basis for biometric pattern recognition systems. The modality (physiological feature) chosen for recognition depends on many factors like uniqueness, ease of registration, time invariance etc... The recognition system that is designed to recognize the humans based on single biometric data, is known as uni-modal biometric system.

Among the various bio modalities available, iris possesses two key advantages over other biometric data. The iris pattern which is formed after two years of age remains static and invariant as long as the user is alive. The iris pattern is found to be unique even among the twins and between the two eyes of the human vision system. The variation of iris pattern among the same class members known as intra class variation is large compared to the variation of iris pattern between members of different class known as inter class variation. Due to these advantages, the difficulty of registering the iris pattern from the users is accepted in most of the cases. The pattern recognition system has three important subsystems as shown in figure 1. The pre-processing sub system removes the noise and unwanted portion of the input iris data. Required part of iris is extracted using this module. The extracted portion is applied to feature extractor module. The accuracy of the entire pattern recognition system depends solely on uniqueness of the features extracted from the processed portion of the eye image. With the help of the features extracted known as template, the classifier makes the decision about the input data's legitimacy.

In general, the pattern recognition system is operated in two modes, namely training mode and testing mode. The extracted features (template) are stored in the database during training mode. During testing mode, the unknown or unseen input is fed as input and decision is made by the PR system. Depending on the decision, the output is classified as "positive" or "negative". Based on the number of instances in which it gives correct results, accuracy of the pattern recognition system is determined. The parameters used to measure the performance of the pattern recognition system are true positive, true negative etc. The flow of the paper is described as follows. In Section II the existing systems are reviewed and the proposed system is described in section III. The experimental results are discussed in section IV. The conclusion and the inference are presented in section V.

II. EXISTING SYSTEMS

The earliest effective implementation of the biometric recognition system using iris pattern is designed and analyzed by J.Daughman et.al [1, 2]. In his work, using integro differential operator, the iris pattern between the white segment of the eye, known as the sclera and the black portion, known as pupil is extracted. Usingthe rubber sheet model, the data which is in annular region is converted in to linear scale. Gabor filters are the used as feature extractor and using bit encoding technique, the binary feature vector known as iris code is constructed. Hamming distance is used as the dis-similarity index to separate the legitimate users from the imposters.

Lye Will Liam and Ali Chekima [3], applied the iris image to contrast enhancement as a pre-processing step. After pre-processing, a circular mask with a thickness of one pixel is created. Using the above mask, the parameters of the iris (center coordinates, radius) are found. Using the iris center coordinate and radius, the iris was segregated. For this segmentation process, the authors used the square window method.In another system [4] developed by Bradford Bonney and Robert Ives, morphological processing steps like dilation and erosion were applied in the iris segmentation process..

Lu Chenghong and Lu Zhao yang [5], have proposed another method for feature extraction.They developed a method to extract blob features of iris. By convolution of iris image with Gaussian filters of different variance, image features are obtained.Jie Wang [6] proposed a system in which the iris texture is extracted by applying wavelet packet transform (WPT) over the image. From the resultant sub-images, few sub-images are chosen. The WPT coefficients of these sub-images are encoded to create an iris code.

Using Discrete Wavelet Transform as feature analysis and extraction tool, Sankowski et al. [7] have designed an iris recognition system.Liam et al. [8] proposed a recognition method using unsupervised learning and Self Organized Feature Map as neural pattern classifier.

III. METHODOLOGY

In the design of a pattern recognition system, when only one modality is used, it is referred to as a uni-modal biometric pattern recognition system. Though the system is easier than other systems toimplement, the obtained uni-modal systems are prone to impairment of noisy output produced by sensor, image degradation and the volatile nature of the traits. Compared withunimodal biometric systems, multimodal biometric systems offer wide benefits such as (i) reduction in error rate reduction (ii) improvement in the availability of the biometric data as loss of one trait is compensated by the other trait information (iii) the ability to authenticate the user in the presence partial availability of biometric traits(iv)less susceptibility to spoofing attacks.

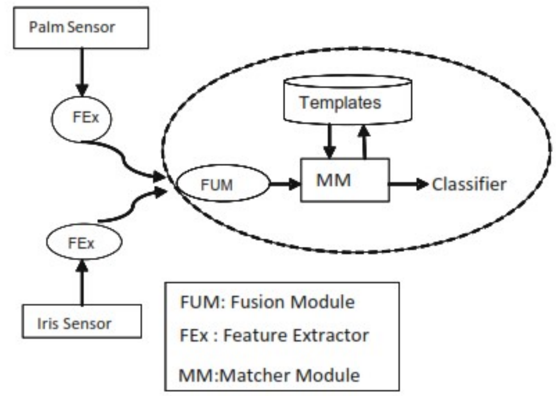


Fig. 1 Structure of multimodal biometric system

Figure 1 shows the functional block diagram of a multimodal biometric system. The structure of a multimodal biometric system is shown in Fig. 1. Generally, there are five different subsystems are present in a biometric system. They are sensor module, preprocessing module, segmentation module, feature extraction module and pattern matching module. The role of each sub module is briefly explained below. To record the biometric data sensor module is used. The enhancement of the obtained biometric data is carried out by preprocessing module. The features are extracted by the feature extractor module. The classification is performed by classifier module. The multimodal pattern recognition system has two uni modal systems namely iris recognition system and palm print recognition system. The system is designed and implemented using Marla 2016a [8] by the authors 1 and 2 and is described here for clarity.

I. Iris Pattern Recognition: An iris recognition system has four modules namely iris localizer for detection and location of iris pattern from the eye image, iris normalization module which transforms the iris data into linear scale, code creator to convert the textural information obtained in the second module into a sequence of binary values, and pattern classifier module for matching or classification.

1. Iris localization

In the first step of iris extraction process, localization of iris portion is carried out. The zig-zag portion which lies between the pupil (black portion of the eye image) and sclera (white portion of the eye image which encapsulates the nerves of the vision system) must be extracted. For this process, the integro differential operator (IDO) created by J.Daughman [1,2] is used. The mathematical expression is given below.

$$\max_{(r,i0,j0)}\left|Ge_{\sigma} * \frac{\partial}{\partial r}\oint_{r,i0,j0}\left(\frac{l(x,y)}{2\pi r}\right)ds\right| \qquad (1)$$

where l(x, y) is the output data from sensor. The operator scans the entire image plane (x, y). By performing the contour integration over the entire image plane (x, y), which varies as radius of the eye disc, it detects the maximum value of region under study by convolving with Gaussian filter Ge_{σ}. As a result the outer boundary of the sclera and inner boundary of the pupil are detected, and circles of appropriate radius and respective center (x, y) are drawn. The original input image and output of localization step i.e images with circles are shown in following figures 1 and 2

Figure 1a. Iris image 1 Figure 2a.Iris Image 2

Figure 1b. Localization Figure 2b. Localization
of Iris image1 of Iris Image 2

2. Iris Normalization

The next step of iris detection is enrollment of iris data. At the output of the first step, iris information is described in the form of circular data (radius, center). They must be converted from the annular co-ordinates into linear co-ordinates (from circular to rectangular). By drawing circles with various radius over the eye image with pupil center as the initial point and sclera center as the final point, the information is extracted. The mathematical expression are listed below.

$$x = ce(x) - ra * \sin(\theta)$$

$$y = ce(y) + ra * \cos(\theta) \qquad (2)$$

Where ce(x, y) denotes center coordinates, (x, y) denotes coordinates of the image, θ is the angle and radenotes the radius. The normalized iris data is shown in figure 3a and 3b.

Figure 3a. Normalized Iris Data (Extracted Iris Data) of Fig 1.a

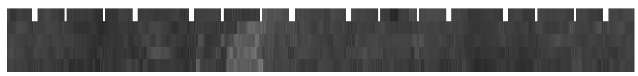


Figure 3b. Normalized Iris Data (Extracted Iris Data) of Fig 2.a

3. Iris feature extractor

From the output of second module, the textural features are extracted by applying discrete wavelet packet transform in which wavelet packet is used. By applying wavelet packet, the region of interest can be selected at any level whereas in the case of discrete wavelet transform always the output of low pass filter only (the coarse sub image) is selected. The wavelet packet decomposition is applied for three levels. At the end of third level, 84 sub-images are obtained. The required features are located in sub images 42,43,44,45. These sub images are the vertically filtered output at the third level of wavelet packet decomposition. From these sub-images, values of Gray Level Dependence Matrix(GLDM) are calculated. The GLDM values are stored in a text file for applying to hardware module. From these GLDM values, textural features are calculated.

Texture is one of the vital characteristics used in the identification of objects or regions of interest in any type of image. In the case of iris image, the variation in the texture of eye’s iris portion is pre dominant than in other biometric images like face or vein. Thus using texture as one of the feature, iris patterns are classified in to different classes.

As described in the work [10] analyzed by M.Haralick and K.Shanmugam, the GLDM matrix is determined. In this proposed work, GLDM matrix and the subsequent textural features are derived by considering horizontal neighboring cells (0^0) with distance of one cell (d=1). The gray tone in each resolution cell is quantized to eight levels (N_g =8).

A total of 4 textural features are extracted from the GLDM matrix. The following equations define the textural features.

$$\text{Angular Second Moment(ASeM} = \sum_{i=1}^{m}\sum_{j=1}^{n} P(i,j)^2 ...(3a)$$

$$Contrast = \sum_{i=1}^{m}\sum_{j=1}^{n} (i-j)^2 P(i,j)^1 ..(3b)$$

$$Disimilarity = \sum_{i=1}^{m}\sum_{j=1}^{n} (i-j) P(i,j)..(3c)$$

$$Variance = \sum_{i=1}^{m}\sum_{j=1}^{n} (i-\mu)^2 P(i,j)..(3d)$$

The extracted feature vectors are binarised, merged and converted into an iris code vector.

4. Iris pattern matcher

The classifier which compares the iris codes of two different persons or two different classes to find out the dis-similarity between them is called “Dis-similarity classifier”. The distance between the code vectors are calculated. Thus it is known as distance based similarity index. Hamming Distance Classifier (HDC) is one among such dis-similarity distance classifiers. The mathematical equation of modified hamming distance (MHD) is given in equation (4).

$$MHD = \frac{codeA \otimes codeB}{n} \quad ....(4)$$

In (4) code A and code B are the iris codes of two irisinput data to be compared, × denotes bit wise exclusive OR operation and n is number of bits in code A and code B.

IV. PALMPRINT RECOGNITION

In palmprint recognition, the required image of the palmprint is obtained by applying preprocessing step and segmentation. The texture features of the palmprint are extracted using Gabor filters. The general form of Gabor filter is shown in equation [5].

$$G(x, y, \mu, \omega, \theta) = \frac{1}{2\pi\sigma^2} \exp\left(\frac{-x^2 + y^2}{2\sigma^2}\right) \exp(2\pi i) * (\mu x \cos\theta + \mu y \sin\theta) \quad (5)$$

where μ is the frequency of the sinusoidal wave, q is orientation control and s is standard deviation of Gaussian envelope. Figure 5a shows pre-processed palmprint. Each output image pixel is encoded into two bits as shown in Figure 5b. The bits in the code matrix are calculated based on the phase value of feature vector resulted due to Gabor filtering.

For each palmprint, size of the generated palmprint code is 1408 bits. The matcher module used in the palmprint recognition system is developed based on hamming distance classifier. The performance of the palmprint recognition system using gabor kernel is shown in figure 6.

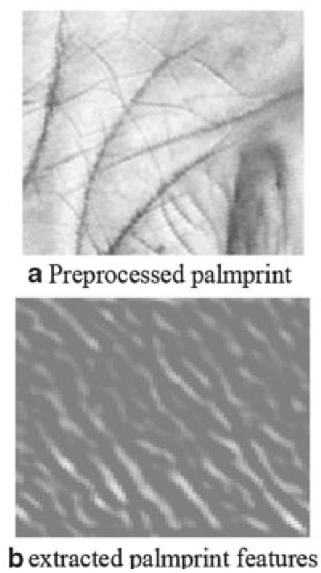


Figure 5. Palmprint output

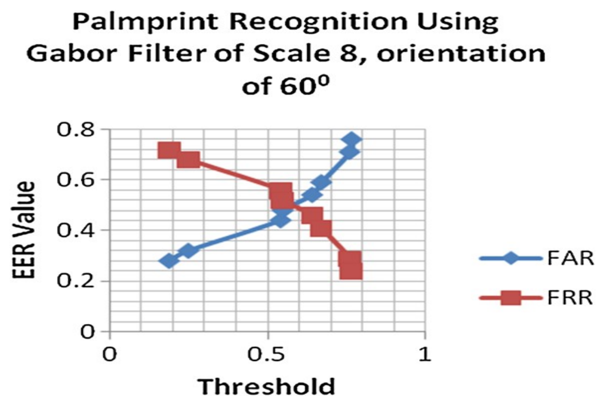


Fig. 6 Palmprint recognition performance using Gabor filters

V. MULTIMODAL RECOGNITION SYSTEM

In the proposed multimodal system, Gray Level Dependence Matrix (GLDM) calculations [9] are appliedfor the extraction of texture content from iris and palmprint. From the sub images that possess the highest entropy, the textural features are determined. From the extracted features, six iris features and four palmprint features are selected. These are combined on horizontal scale to create a ten element pattern vector. This feature vector is binarised into a sequence of 1 and 0s. The resultant code vector is called iris palm print multimodal pattern vector (IPMPV).

VI. DESIGN OF TEXTURAL FEATURE EXTRACTOR (TFE)

The four textural features denoted in equation 3a- 3d are implemented in the hardware. FPGA is an array of thousands of programmable logic gates arranged in a specific structure. The analysis of equation 3a (expression for Angular Second Moment) reveals that squared circuit is required in the hardware. The multiplication by a factor of two can be implemented as linear left shift operation. Thus the need of large gates are minimized.

By similar analysis of other equations, the required logic can be implemented with summation unit, subtractor and shifter modules. Table A lists out the required modules for efficient implementation of the various sub operations of equation 3a to 3d.

Table A. Hardware modules for sub operations of haralick features

S.No	Expression	Module
1.	$(i-j)^2$, $p(i,j)^2$, $(i-\mu)^2$	Left shifter by one bit
2.	Double summation	Counter (3bit)

From the above table, it is found that the following modules are required as hardware element.
1. Left shift module – three modules
2. Three bit counter- four module
3. Multiplier – one module

The above modules are implemented as RTL code using VHDL 2008 language. In section four, the results are shown.

VII. DESIGN OF HARDWARE PATTERN CLASSIFIER

Hamming distance classifier is applied to find out the dis-similarity among the two IPMP vectors. The Iris Palmprint Multimodal Pattern Vector (IPMPV) are stored in the ram. The size of each code vector is 1480 bits. These bits are stored as one byte information in each location of the random access memory designed. Thus the ram should be having minimum 185 locations. As IPMPV from 10 classes are to be stored, the minimum number of locations required are 1850 locations. As a standard size a ram of 2048x8 is designed. Using timing and instruction unit, the information from each location is fed to the buffer memory and applied to XOR gates.

The code is developed using Verilog HDL. It is shown in figure 7.

```
module xorbank(ainput,binput,xoroutput)
input [184:0]ainput,binput;
output[184:0] xoroutput;
begin
assign xoroutput = ainput ^ binput;
end
endmodule
```

Figure 7. HDL code for bank of XOR

After performing the XOR operation which identifies the bit positions in which code A and code B differs from each other, total number of such locations are to be counted. Hence a counter of 10 bit is designed. Verilog HDL code for the ram designed is shown in the figure 8.

```
module memorybank (IPMPvectoroutput,
IPMPvectorinput,readwritebar,clk,reset,addr_loc)
output reg[7:0] IPMPvectoroutput;
input [7:0] IPMPvectorinput;
input[11:0] addr_loc;
intput readwritebar,clk;
reg  [7:0] patternvectorbank[0:2047];
always @ (posedge clk)
begin
if(readwritebar)
  IPMPvectoroutput=patternvectorbank[addr_loc];
 // data is put into output bus;
else
patternvectorbank[addr_loc]=IPMPvectorinput;
end
endmodule
```

Figure 8. Verilog HDL code for memory bank used

The addr_loc is the control signal that indicates the location of the memory in which the IPMPV is stored and retrieved is supplied by control unit. The data path unit of the hardware chip contains the following modules.
1. memory bank of size 2k words with one byte width in each location
2. A bank of xor gates bank consists of 185 xor gates.
3. A data counter to count 8 clock pulses
4. an address counter to count 10 clock pulses.
5. A memory buffer of 370 bits to store the intermediate results of xor comparison.
6. a 4:1 multiplexer to control xor gate, adder of 2 kinds.
Using the moore machine style of Finite state machine the control path signals are generated.

4. Results and Discussion

The results of the uni modal system designed and multi modal system designed in this work are tabulated in table 1.

Table 1 Recognition performance of iris feature vector with different wavelet packets

Wavelet type	Accuracy in %	Length of feature vector
haar	84.00	294
daubechies	86.00	720
Symlets14	89.00	784
bior 1.3	85.00	784
bior 2.8	93.00	1600
bior 6.8	93.50	1728
coif2	91.00	1408
coif3	92.50	1408
Symlets20	92.50	1408

In table 2 shown below the performance metric of palm print are listed out.

Table 2 Recognition performance of palmprint feature vector with different threshold values

Threshold	FAR	FRR
0.1866	0.24	0.76
0.2575	0.31	0.69
0.5498	0.42	0.58
0.5464	0.48	0.52
0.6400	0.52	0.48
0.6615	0.59	0.41

In table 3, the multimodal pattern recognition system performance is shown

Table 3 Multimodal biometric performance for variation in length of feature vector

Modality	Accuracy in %	Length of feature vector
Iris	92.00	1408
Palmprint	87.00	1408
Iris and Palmprint	94.50	1408

In table 4, the delay and hardware resources computed for the proposed Modified Hamming Distance Classifier (MHDC) is listed out.

Table 4. Device utilization report for MHDC

Selected Device : 4vlx15sf363-12			
Hardware elements	Used	Total available	%
Slices	49	6144	0.007
Flip flops	64	1288	0.049
4 input LUTs	64	1288	0.049
RAMs	16	--	--
No of IOs	185		
Bonded IOs	185	240	35.41
GCLKs	1	32	3.2
DSP48s	1	32	3.2

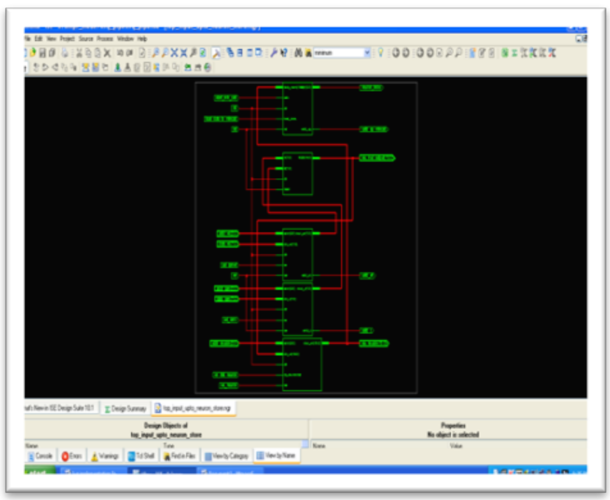
In table 5, the delay and hardware resources computed for the proposed Textural Feature Extractor (TEF) is listed out.

Table 5. Device utilization report for TEF

Selected Device : 4vlx15sf363-12			
Hardware elements	Used	Total available	%
Slices	1214	6144	19.75
Flip flops	260	1288	12.48
4 input LUTs	260	1288	12.48
RAMs	32	--	--
No of IOs	225		
Bonded IOs	225	240	93.75
GCLKs	1	32	3.2
DSP48s	4	32	12.35

In figure 9, the RTL diagram of the designed MHDC is given.

Figure 9. RTL diagram of the MHDC



VIII. CONCLUSION

In the proposed design, when biorthogonal wavelets are used as wavelet in DWT transform and WPT transform, the size of the IPMPV is significantly reduced at the cost of decrease of three percent accuracy.In Hardware implementation of HDC, the basic blocs required are bank of XOR gates and counters. The inputs applied are having a size of 1480 bits.Using Moore model FSM, the control signals are generated and counter as well XOR gates are controlled. Multiplexer is used as a selection unit to control the sequential and combinatorial blocks. Hence the area occupied in terms of LUTs is reduced. This produces an optimal implementation of area in FPGA

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