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Fpga Implementation of Hybrid Face Recognition System Based On Real and Imaginary Kernels of Rotational Invariant Transform

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ABSTRACT

Gabor filter is mainly used to design features for recognition of face images. To enhance the effectiveness of face representation through feature design (Gabor Filter), the parameters mask size, scale and orientation are very important. This paper investigates the effect of different Gabor filter parameters on face recognition. Moreover, this paper proposes a novel rotation algorithm to make the slanting face to upright position, which increases the face recognition accuracy. With regard to the hardware implementation, two architectures for two-dimensional (2-D) Gabor wavelet transform with only real kernel and both real and imaginary kernels have been synthesized using VHDL and implemented on Xilinx Virtex-5 FPGAs. Experimental results on different data sets of face images and a detailed performance analysis of the area, maximum frequency and power consumption are also discussed in this paper. **Keywords:** Field Programmable Gate Array (FPGA), Gabor Wavelet Transform (GWT), Optimal Ratio Average (ORA), Face Recognition Accuracy.

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INTRODUCTION

Face recognition plays an important part of the biometrics technique, and it is very useful in scientific research . This biometric technique has the ability to identify a person based on his/her facial characteristics. Machine recognition of faces is applicable in the active research area disciplines such as image processing, pattern recognition, computer vision and neural networks. Face recognition technology has numerous applications ranging from static matching of controlled format photographs such as passports, credit cards, photo IDs, driver's licenses, and mug shots to real time matching of surveillance video images.

Face recognition using Gabor filters was first introduced by Martin Lades *et al*. (1991) and soon proved to be a most effective method by using human facial feature extraction.The face recognition using Gabor wavelets has several advantages such as invariance to some degree with respect to translation, rotation and dilation. Furthermore, it saves neighbourhood relationships between pixels, is robust against illumination when face is normalized correctly, is robust against noise, is easy to update, and has fast recognition and low computational cost. The significance of this area would be to provide a basis for future development of many applications such as aids to security, surveillance, digital personal assistant and camera-equipped cell-phones, which require personalized face recognition systems.

Gabor filters and the wavelet transformation are applied on the input patterns to extract the important features and reduce the dimension, and then discriminative common vectors are obtained using within-class scatter matrix. This dimension of the feature vectors is very high when applying the Gabor wavelet to the input image through a convolution process. This dimension problem can be solved by subspace projection which is usually used to transform the high dimensional Gabor feature vector into a low dimensional Gabor feature vector. Gabor wavelets or Gabor filters have the characteristics for frequency and orientation representations which are mostly similar to those of human visual system. These have been found very appropriate for texture representation and discrimination. Gabor wavelet-based features are extracted directly from the gray level images and are widely used in texture segmentation and fingerprint recognition.

Gabor wavelet, the most useful transform in face recognition, which focuses on the properties of

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orientation selectivity, spatial localization and optimally localized in the space and frequency domains, has been extensively and successfully used in face recognition (Jian Wang, 2010). Due to its important role in a number of application domains such as access control, and visual surveillance, automatic face recognition has been extensively studied over the past two decades (Faten Bellakhdhar, 2013).

Matthew Turk *et al*. (1991) presented a near-real-time face recognition system in which Eigen faces in facial image feature extraction were introduced. Chengliang Wang *et al*. (2011) proposed an effective recognition technique using Principal Component Analysis and Support Vector Machine.

Xiao-ming *et al*. (2009) proposed a face recognition algorithm combining vector features consisting of the magnitude of Gabor and PCA, and classification is done by SVM . Arindam Kar *et al*. (2011) have proposed a method in which high intensity feature vectors are extracted from the Gabor wavelet transformation of frontal face images and they are combined with Independent Component Analysis (ICA) for enhancing face recognition.

Shen *et al*. (2008) have presented a frame work based on a combination of Gabor wavelets and General Discriminant Analysis for face identification and verification. Wing-Pong Choi *et al*. (2011) proposed a simplified version of Gabor wavelets (SGWs) and an efficient algorithm for extracting the features based on an integral image .Xiaofei *et al*. (2011) presented Locality Preserving Projections to describe face images by mapping the face data onto a low-dimensional face feature subspace which is called "Laplacianfaces".

The effective face representation is achieved by (Zhang, Kaisele, Kim and Liaund, 2006 & 2007), fusing features from different bands, features are derived from different scales, using both geometrical and statistical features, and fusion of Gabor pattern with Local Binary Pattern were done in the previous approaches. The Gabor features consist of magnitude and phase parts. The phase-based works generally give worse results than those using magnitude.

This paper proposes a novel rotation algorithm and the best choice of Gabor filter parameters, which design Rotated Local Gabor Phase patterns(RLGP). Then, the Rotated Local Gabor Phase XOR pattern (RLGXP) is designed by using XOR pattern operator (Kannan. P. *et al*. 2014), which encodes Rotated Gabor Phase patterns. Inorder to reduce the dimensionality of RLGXP descriptor, the scorelevel fusion and feature level fusion techniques are used (Shan and Su, 2006 & 2007). The whole features of an image in the feature space are divided into number of smaller blocks. The dimensionality reducation operation is performed on each block. Then, Rotated local patterns of Gabor magnitude and phase are fused together and used their significant information to achieve perfect face representation for face recognition. The experiment are carried out on the three datasets namely MIT, GTAVE and home images by using various Rotated local Gabor patterns and using two-different fusion schemes. The comparative experimental studies shows that the proposed RLGXP feature descriptor achieves better results than the other methods in different cases, and the performance is highly improved by the application of fusion schemes.

This paper proposes hardware architectures for two-dimensional (2-D) Gabor wavelet using only real kernels and both real and imaginary kernels. Xilinx Virtex-5 is used to implement the proposed architectures and examination of the transform size influence on the area, power consumption and maximum frequency are also carried out.

The remaining section of the paper is organized as follows: An overview of the algorithms and methodology are presented in Section 2. Section 3 summarises the results that have been obtained through two experiments: Gabor Wavelet parameter selection and Fusion approach. Hardware implementation and results obtained for the proposed architectures are also described in Section 3. Finally, concluding remarks are given in Section 4.

2 Algorithms and methodology:

An overview of the algorithms and design methodology for the software as well as hardware implementation are presented in the following sections.

2.1 Gabor patterns:

A group of wavelets is combined together to form Gabor filters. The convolution operation is performed on the given image with Gabor coefficients, a set of filtered images is obtained. The convolution results represents the information of an image with certain scale and orientation. Gabor features can be calculated from each filtered image and be used to retrieve images (Dengsheng Zhang, 2004)

For a given image I (x , y) with size P x Q, its discrete Gabor wavelet transform is given by the convolution.

$$G_{mn}(x,y)=\sum_s\sum_t I(x-s,y-t)\Psi^*_{mn}(s,t) \tag{1}$$

.

where, s and t are the filter mask size variables, and ψ^*_{mn} is the complex conjugate of ψ_{mn} which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet.

$$\Psi(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2}\right)\right]\exp(j2\pi Wx) \tag{2}$$

where 'W' is called the modulation frequency. The self-similar Gabor wavelets are obtained through the generating function

$$\Psi_{mn}(x,y)=a^{-m}\Psi(\tilde{x},\tilde{y}) \tag{3}$$

where m and n specify the scale and orientation of the wavelet respectively, with m=0,1,……..M-1, n=0,1,…….,N-1 and

$$\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)$$
$$\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta) \quad (4)$$

where a>1 and θ = nπ/N.

The variables in the above equations are defined as follows.

$$a = (U_h / U_l)^{\frac{1}{M-1}},$$
$$W_{m,n} = a^m U_l$$
$$\sigma_{x,m,n} = \frac{(a+1)\sqrt{2\ln 2}}{2\pi a^m (a-1)U_l},$$
$$\sigma_{y,m,n} = \frac{1}{2\pi \tan\left(\frac{\pi}{2N}\right)\sqrt{\frac{U^2{}_h}{2\ln 2} - \left(\frac{1}{2\pi\sigma_{x,m,n}}\right)^2}} \quad (5)$$

The dimension of the filter mask is $s \times t$. U_h = 0.4 and U_l=0.05 are chosen in this work.

2.2 Local Binary Patterns (LBP):

Every pixel of an image is assigned by a label with the help of LBP operator and by the thresholding operation of the 3 × 3 neighborhood of each pixel with the center pixel value (Su *et al*. 2007). One pattern map of an image is obtained by applying LBP operator on the facial image. The description of the input facial image is formed by dividing the pattern map into a number of blocks,computing the histogram of each block and concatenating the computed histogram of each block together (Ahonen *et al*. 2005)

2.3 Local Gabor Patterns (LGP):

Initially, the Gabor real and imaginary kernels are convolving with the input facial image, Gabor real and imaginary coefficients are obtained.Then, encode the Gabor real coefficient and imaginary coefficient using LXP operator correspondingly Local Gabor Patterns are obtained.Likewise, encode the Gabor magnitude and phase feature via LBP operator, local Gabor magnitude and phase patters are obtained. The local Gabor patterns Re_LGPP, Im_LGPP, LGBP_Mag (Zhang *et al*. 2006) and LGBP_Pha (Zhao, 2003) are obtained by these encoding techniques.

2.4 RLGXP: Rotated Local Gabor XOR Patterns:

A. Rotation Algorithm:

At first, the slanting face is sorted out from the original image. The right and left eyes are cropped out in the rectangle shape and the line is drawn between the centres of the rectangle of both eyes. The length of the line is measured by the following formula

$$d = \sqrt{(crighteye - clefteye)^2 + (rrighteye - rlefteye)^2} \quad (6)$$

It is observed that from the distance of the line, the slope is measured and the angle θ can be calculated. It is to be identified whether the face is slanting towards left or right and if it is slanting towards the left side, the image has to be rotated in the anticlockwise direction. The rotation angle is given by

$$\theta' = -\theta * \frac{\pi}{180} \quad (7)$$

If it is slanting towards the right side, the image has to be rotated in the clockwise direction. The rotation angle is given by

$$\theta' = \theta * \frac{\pi}{180} \quad (8)$$

Neural Network Training algorithm is used for carrying out the rotation.Then, the Gabor Magnitude and Phase features of the facial image are calculated by the design procedure depicted in 2.1.

B. RLGXP Descriptor:

The Rotated Gabor phase value is evaluated by the following formula.

Rotated Gabor Phase: $\Phi_{\theta,v}(x, y) = \arctan[Im_{\theta,v}(x, y)/Re_{\theta,v}(x, y)]$ (9)

where 'θ' is the orientation factor and 'v' is the scaling factor

The accumulated Rotated Gabor phase value is quantized. The quantization is done in the following ways:

(i) If $0° \le \Phi_{\theta,v}(x, y) \le 90°$, *Quantized value = 0*
(ii) If $91° \le \Phi_{\theta,v}(x, y) \le 180°$, *Quantized value = 1*
(iii) If $181° \le \Phi_{\theta,v}(x, y) \le 270°$, *Quantized value = 2*
(iv) If $271° \le \Phi_{\theta,v}(x, y) \le 360°$, *Quantized value = 3*

After quantization of Rotated Gabor phase value, Local XOR pattern operator is used to extract the face features. The LXP is performed over the quantized phases of the central pixel and each of its neighbors, and by executing this result, binary labels are concatenated as the local pattern of the central pixel.

A pattern map is calculated for each Gabor kernel with the pattern defined in the aforesaid section. Then, a number of nonoverlapping sub-blocks is generated by dividing the each pattern map, and the histograms at all the scales and orientations of the all the sub-blocks are concatenated to form the proposed RLGXP descriptor of the input face image. In this paper, Gabor filters of five scales and eight orientations are used. Then for face recognition, the similarity between two RLGXP descriptors can be calculated.

2.5 The proposed feature vector dimensionality reduction:

The proposed RGLXP descriptor cannot be directly applied to face recognition by using similarity measurement when the dimension of feature vector size is 40 (5 scales, 8 orientations). In order to reduce the high dimensionality, Block-based Fisher's Linear Discriminant(BFLD) can be used directly.

Gabor magnitude and phase provide complementary information to distinguish different

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human faces. In order to improve the recognition accuracy, the local patterns of Rotated Gabor magnitude and phase, i.e. RLGBP_Mag and RLGXP are combined. Briefly speaking, they are fused by using dimensionality reduction technique at two levels, i.e. feature level and score level.

Both feature level and score level fusion methods are conducted on block level. In the case of feature-level fusion, for each block, the histogram representations of RLGBP_Mag and RLGXP are simply concatenated into one vector, which is then used to extract feature by FLD; based on the extracted features, one similarity can be calculated. In contrast, for the score level fusion, for each block, two low-dimensional vectors are respectively extracted from the histogram representations of RLGBP_Mag and RLGXP by FLD, and then used to compute two separate similarity scores; finally, these two scores are fused as the final score. The sum rule is used to calculate the similarity between gallery and probe face images. The face classification can be done by the thresholding technique.

3. Experimental Results:

The significant characteristics of Gabor filter in frequency domain are frequency and orientation selectivity. The shape of the characteristics curve is Gaussion model. The band of frequency components of an image can be derived with different values of scaling parameter. The directional features can be extracted from an image with various values of orientation parameter. The multiplication of the number of scales and the number of orientations gives the total numbers of features derived from an image (Dengsheng Zhang, 2004)

A. Sensitivity analysis of Gabor wavelet parameter Selection:

The performance of the proposed work on the face recognition system is evaluated on different test sets of face images by two ways:

(i) Size of Mask is constant with different scales and orientations.

(ii) Various filter mask sizes with constant scale and orientation.

In Fig.1, the graph for M2S5O8 represents filter mask size of 2 x 2, scale of 5 and orientation of 8(the total number of filters or features is 40), for various test data sets with different variability. The performance of face recognition accuracy is affected by different combinations of scales and orientations even if the filter mask size is the same (Dengsheng Zhan, 2004).

The experimental results also suggest that the larger number of scales and orientations do not provide better performance as shown in Fig. 1. The performance of M2S4O16 is nearly the same as that of M2S5O8, but it is more expensive than M2S5O8 since it needs larger number of computations. Moreover, Fig. 1 shows that the less number of features(M2S8O2) do not give better performance than M2S5O8. Therefore, the best face recognition accuracy is achieved by the mask size of 2 × 2 with 5 scales and 8 orientations. Further, if the number of filters is large, the more detailed and redundant features can be extracted from the image. But this can't provide good recognition performance due to similar features can be extracted by different filters. In the contrary, small number of filters cannot provide sufficient information about the images. Thus, the selection of number of filters is essential and it should not be very large and very small.

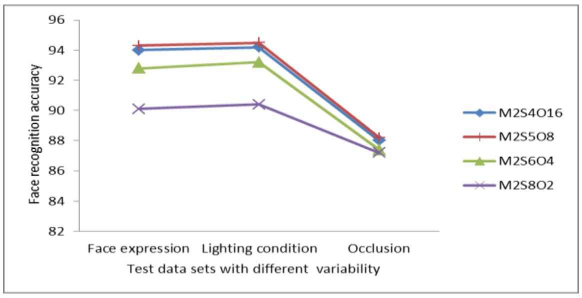

Fig. 1: Mask size 2 x 2 with different scaling and orientations.

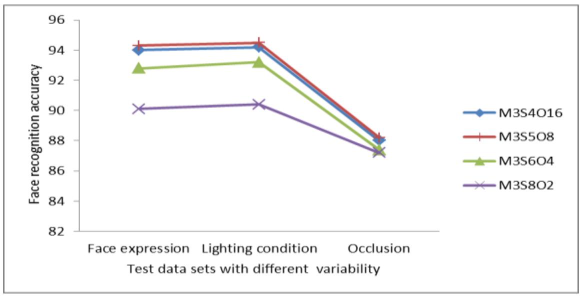

Fig. 2: Mask size 3 x 3 with different scaling and orientations.

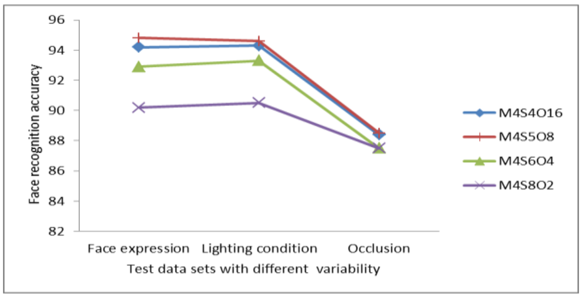

Fig. 3: Mask size 4 x 4 with different scaling and orientations.

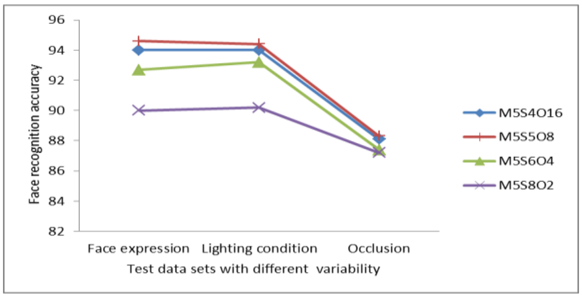

Fig. 4: Mask size 2 x 2 with different scaling and orientations.

With the consideration of analyzing parameters of both face recognition accuracy and computational cost, the combination of scale 5 and orientation of 8 is the best choice for filter mask size of 3x3 and 5x5 respectively which is shown in Fig. 2 to Fig. 4.

The Gabor features of an image can be computed by convolving Gabor filters with an image. If the image size is large, convolution takes much time and gives more computational complexity. The computational speed of the convolution is operation is domain dependent. Therefore, the convolution operation is performed in frequency domain which increases the computational speed than the same operation is performed in the time domain. Initially, the Fast Fourier Transform is performed over the given image and Gabor filters individually. Then, the product of the both the results takes place. Finally, the convolution results are obtained by taking the Inverse Fast Fourier Transform of the product. Furthermore, the computational complexity arises as well as the requirement of large storage space is needed when the number of Gabor filters is large. So, the number of filter selection is an essential.

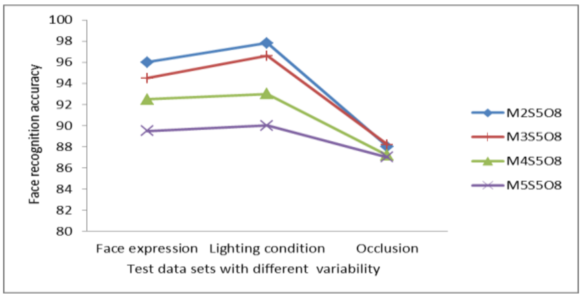

Fig. 5: Scale: 5, Orientation: 8 and various mask Size.

In Fig. 5, the experimental results with various filter mask sizes are shown. The filter mask size of 3x3 provides the best performance whereas the filter mask of size 5x5 gives the worst performance. If the mask size is large, it requires large number of neighborhood image pixels for the whole convolution process at a point of an image. Due to this, some unrelated pixels are subjected into the convolution operation, it arises non-homogeneous patterns. Therefore, the recognition of facial image may not be accurate if the filter mask size is large. In the contrary, if the filter mask size is too small, there is a chance of missing of some related pixels. So, the recognition cannot be accurate if the neighborhood is too small. As a result, the effective recognition also cannot be achieved. Fig. 6 shows that M2S5O8 performs more or less same performance as that of M3S5O8. Therefore, the filter mask size 3x3 is the best selection for the proposed system, since the filter size neither too large nor too small. The filter mask size is too high computational cost is high but the computational speed is very low.

B. Performance analysis of fusion approach:

The feasibility and performance of the proposed novel RGLXP on the face recognition work is assessed using different test sets of images collected from AR, MIT, PIE, CVS, GTAVE and home images. The images are acquired under variable illumination, different facial expressions, poses and may be even partially occluded.

Table 1: Recognition Accuracy of Different Approaches on different data test sets.

Method Category	Methods	Probe Sets		
		MIT	GTAVE	Home images
Rotated Local Gabor Patterns	RLGBP_Mag	95	94	96
	RLGBP_Pha	96	96	96.5
	RRe_LGPP	97	97.5	97.5
	RIm_LGPP	97	97.5	98
	RLGXP	97.5	98	98
Rotated Local Gabor Patterns+BFLD	RLGBP_Mag+BFLD	96	95	97
	RLGBP_Pha+BFLD	97	97	97
	RRe_LGPP+BFLD	98	98.5	98.5
	RIm_LGPP+BFLD	98	98.5	99
	RLGXP+BFLD	98.5	99	99
Fusion of Different Gabor Parts	S[RLGBP_Mag+ RLGBP_Pha]	98	98	98
	S[RRe_LGPP+RIm_LGPP]	98	98.5	98.5
	F[RLGXP+ RLGBP_Mag]	98.5	99	99
	S[RLGXP+ RLGBP_Mag]	99	99.5	99.5

The three probe sets such as MIT,GTAVE and home images are evaluated by the proposed method, and a detailed comparison is made with different approaches. The parameters for local Gabor patterns are as follows: m=64 (i.e., 8×8), P=4. The parameters for dimensionality reduction- block based approaches are as follows: M=16 (i.e., 4×4), and K=4 (i.e., 2×2). The value of b is set to 4 for RLGXP, and the weight for score-level fusion approach is set to 0.5. The table 1 shows the scorelevel fusion of proposed feature vector provides better results than the fusion by feature level.

Table I tabulates the results of different local Gabor patterns, their combinations with dimensionality reduction scheme as well as their fusion approaches on three different probe sets. Table 1 ,records the following observations: Initially, the proposed feature vector RLGXP performs better than the other rotated local Gabor pattern descriptors; Then, by combining dimensionality reduction scheme, the performances of all local Gabor pattern methods are slightly increased; Finally, fusing various Gabor parts in score-level or feature level, the performance is further improved, and the score-level fusion of RLGBP_Mag and RLGXP produces nearly the best results on all the four probes.

The architecture of the proposed system is coded in Verilog and simulated in Xilinx ISE 14.1. The design has been implemented in a Xilinx Vertex 5 FPGA. Gabor filter is designed to test different data sets with different variability of 9442 faces each of size 15x15 pixels, and each pixel value is represented by 32 bits. The overall architecture of the proposed system with only real kernel and both real and imaginary kernels is shown in Fig. 6 and Fig. 7.

The FPGA implementation results of Area utilization, Maximum frequency used and power consumption summary of Gabor filter with real and imaginary kernels are depicted in Table 2 and Table 3 respectively.

The signal description is as follows.
Input CLK - input clock
nRST - reset active low
en - enable signal for starting image processing
din - input image pixel value output
d_real,d_img = output real and imaginary values
d_ready = if high, the "d_real,d_img" signals are valid to read. (ie output ready to read from bus)
imend = if high, then whole image is sent for processing & RAM is ready to get next image
finish = if high, then entire image is processed.

In the face recognition system, the input of the size of 32bits has been used to examine the transform sizes on the area(slices), power consumption (mW) and maximum speed (MHz). The results obtained by the proposed 2-D Gabor Wavelet architecture using both real and imaginary kernels clearly show that it utilizes more area and consumes more power. Conversely, it provides better face recognition accuracy than those designed using only real kernels.

4. Conclusion:

The four main issues have been addressed in this paper: the parameter selection of Gabor filter mask, the software simulation of a novel feature vector construction approach for face recognition using Rotated Local Gabor XOR Pattern,the feature dimensionality reduction by feature level and score leve fusion approaches and the FPGA implementation of Rotational Invariant Transform block in the face recognition system. The effect of fusion of Gabor phase with its magnitude is investigated in this paper. The proposed method is extensively evaluated on three different test data sets, which indicates that the rotated fusion method gives better or comparable results than without fusion

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method. More efforts are needed in future to improve its performance by using statistical fusion schemes.

On the contrary, two architectures for 2-D Gabor Wavelet Transform with only real kernels and both real and imaginary kernels have been implemented in the proposed face recognition system. To sum up, comparative study for the aforesaid two architectures has shown that 2-D Gabor Wavelet Transform with only real kernels offers many advantages such as number of systems are mapped to small hardware resources and the area, power and maximum frequency are optimized and improved. On the other hand, the feature vectors which are designed from the facial image using 2-D Gabor Wavelet Transform with real and imaginary kernels provide better recognition accuracy than by real kernels. In order to reduce area utilization, power and maximum frequency, the Dynamic Partial Reconfiguration (DPR) techniques can be used in future work.

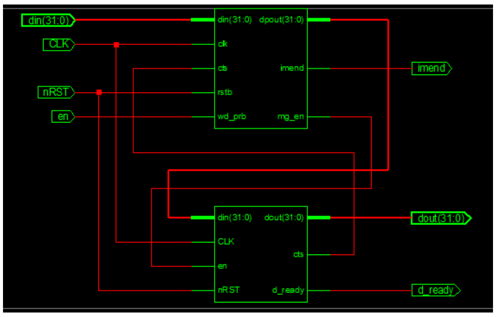

Fig. 6: RTL schematic of Gabor Filter with Real Kernel.

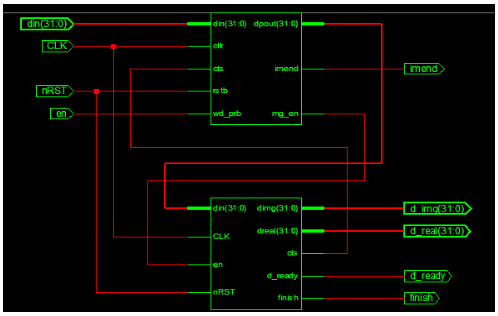

Fig. 7: RTL schematic of Gabor Filter with Real and Imaginary Kernel.

Table 2: Device Utilization Summary of Gabor Filter.

Component	Available	Usage		% of utilization	
		With Real Kernal	With Real and Imaginary Kernal	With Real Kernal	With Real and Imaginary Kernal
Number of Slice Registers	19200	2485	4806	12	25
Number of Slice LUTs	19200	9867	14959	51	77
Number of fully used Bit Slices	15823	2058	3942	13	24
Number of bonded IOBs	220	69	102	31	46
Number of BUFG/BUFGCTRLs	32	16	16	50	50
Number of DSP48Es	32	4	8	12	25

Table 3: Timing and power consumption Summary of Gabor Filter.

Component	With Real Kernal	With Real and Imaginary Kernal
Maximum Frequency	153.900MHz	149.787MHz
Minimum input arrival time before clock	2.158ns	2.203ns
Maximum output required time after clock	3.135ns	17.083ns
Maximum combinational path delay	No path found	17.081ns
Power consumption	502.62mW	1056.83mW

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