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Face Detection by Fine Tuning the Gabor Filter Parameter

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***Abstract*:- Face detection technique recognition is developed by using and fine tuning the Gabor Wavelet parameters. An extensive study of these parameters have been made and checked on a large acquired data set of face images, for extracting the features. The Facial data consists of 320 frontal face 180 non-face images. (Total=500 images) Artificial Neural Network is then used on the extracted features for training. An effect of pixels size of the face on the image was studied. A strong correlation between the pixels size of the Face and the Scaling parameter of Gabor filter was observed.**

***Index Terms*:-Gabor Wavelet, Gabor Filter, Gabor Parameter, Feature extraction, Artificial Neural Network.**

I. INTRODUCTION

The initial motivation of the work was to have a face recognition method placed on robot for identification of persons. In this regard we set out to explore the techniques of face recognition. The object was to that the robot should recognize the target person track him even in a crowded area. To achieve this, the first task has been to detect all faces in the image taken by the robots camera then these faces has to be matched with the target face for identification. While detecting the faces computer scientist had tried earlier to understand the anatomical architecture of the face of human. The most important architecture includes face outline, hair, mouth and eyes. Nose is considered to be least important in terms of remembering and perceiving faces by humans. One of the methodologies to recognize faces is based on geometrical local face features. These methods are usually called Holistic methods. One such Holistic method is PCA technique [1]. PCA means principal component analysis. Another methodology is statistical one. This includes LDA (Linear Discriminant Analysis) [2].
PCA was used with Gabor filter techniques. There are two steps, the first step original image was used to generate the local features of the face on predefined fiducially points. The second step is similar to that used in PCA. The difference is now that in place of the whole face only the generated features were used for the classification of face problem. The co-relation of facial features was not well understood by Eigen vectors. Gabor filter technique removes the aforesaid drawback. The orientation of face will not have an effect on the result if Gabor wavelet technique is used.
In this paper the implementation is of face detection is done through Gabor Wavelet technique [3] for feature extraction from facial, non-facial images and neural network technique for learning process.

II. GABOR WAVELET FILTER

For Face detection using Gabor wavelet, we have created Gabor filter using equation (1) for five different scales V□ {0 . . . 4} and eight different orientation μ □ {0 . . . 7} [4]. Therefore, Gabor filter of 40 images (matrix) has been created is shown in Figure 1, called Gabor faces.

$$\psi_k(z) = \frac{\|k\|}{\sigma^2} e^{-\|k\|^2 \|z\|^2 / 2\sigma^2} [e^{ikx} - e^{-\sigma^2/2}] \qquad (1)$$

Here, k determines the wavelength an orientation of ψ_k (z).The k is defined as

$$k(\mu, \nu) = k_\nu e^{i\phi_\mu}$$

Where, μ and υ define the orientation and scale of the Gabor filter $k_\nu = \frac{k_{max}}{f^\nu}$ and $\phi_\mu = \frac{\pi\mu}{8}$, Kmax is for the maximum frequency and f is for the spacing factor between Gabor filter in the frequency domain.

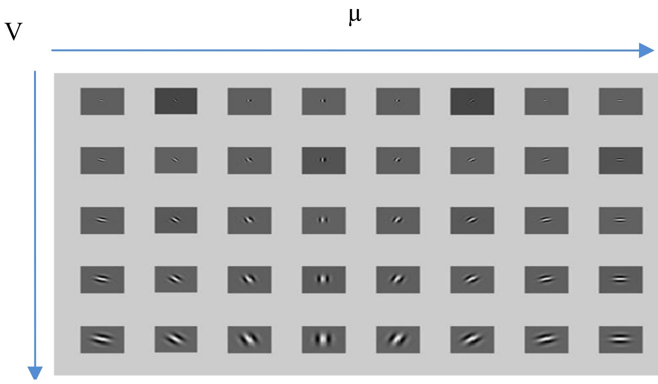


Figure 1 Gabor Filter.

For creation of Gabor filter, we have used these values σ = π, kmax = π and f = sqrt(2) and window size of 32X32 for good result. But, as suggested by Lades and et al. [5] for σ = 2π, kmax = π/2, it's does not give satisfactory result for our database.

III. ARTIFICIAL NEURAL NETWORK

We are using artificial neural network for training our system for face and non-face data feature where our artificial neural network has three layers, one input layer, one hidden layer and one output layer [6] as shown in Figure 2, we have initialized the input range between -1 to 1 and size of hidden layer with 100 . For calculation Hyperbolic tangent sigmoid layer transfer function is used as described in equation (2). For checking the performance of network Mean squared error with regularization performance function is used, which measures the network performance as the weight sum of two factors mean squared error and mean squared weight and bias value. Network training function to train the whole network, we are using Scaled Conjugate gradient back propagation function.

$$A = \frac{2}{(1+e^{-2*n})} - 1 \qquad (2)$$

Here, n is the input to network.

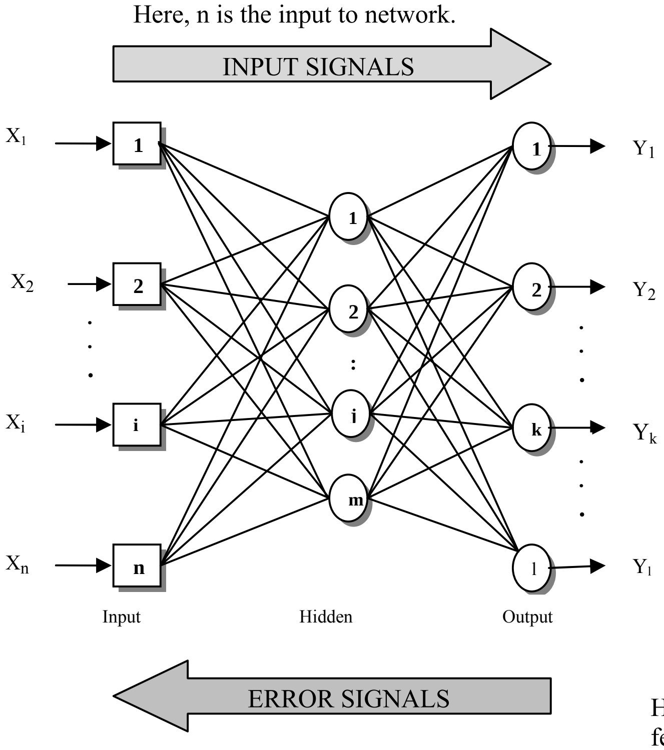


Figure 2 Architecture of Artificial Neural Network.

IV. PRE-PROCESSING

Each face image is edited in 10 different ways and each no-face image is edited in 4 different ways as shown in Figure 3 and Figure 4. So, we have 10 images for each face image and 4 images for each Non-face image.

V. FEATURE EXTRACTION

For extracting features apply 2D Fast Fourier transform in all edited face and non-face image, and also in all Gabor filter. After that calculate O_k (z) using convolution between face and non-face images, let say *I* (z) with a family Gabor wavelet filters ψ_k using equation (3) and normalize it.

$$\overrightarrow{o_k}(z) = I(z) * \psi_k(z) \qquad (3)$$

Here * denotes the convolution operator, and the result is stored in O_k (z) at k.

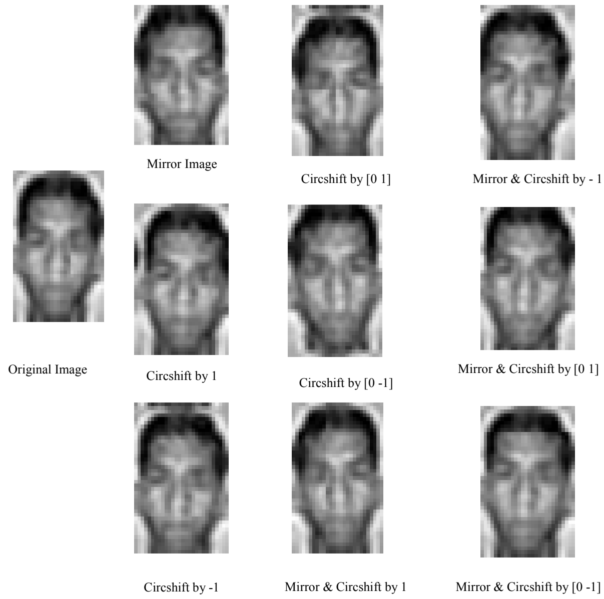


Figure 3 Edited Face Images in 10 different ways.

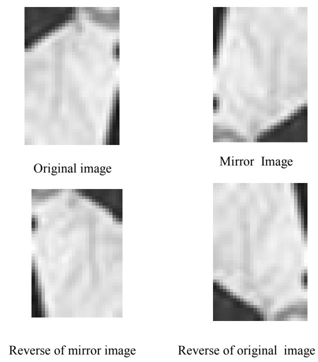


Figure 4 Edited Non-face Images in 4 different ways.

Hence, for 1 edited image there will be 40 normalized featured images as shown in Figure 5 and for 1 face images there will be 400 featured images and for 1 non-face images there will be 160 featured images. For normalizing the featured images find the maximum and minimum value in the featured images $O_k(z)$, of which one is size of 27X18 pixels, after that apply the equation (4).

$$F(z) = \left(\frac{O_{i,j}(z) - min}{max - min} - 0.5\right) * 2 \ \forall 1 \le i,j \le m,n \qquad (4)$$

Combine all the normalized 40 featured images of 1 edited image and compress it. To reduce the computational complexity, we have reduced it to 45X48 from 40X27X18. After reducing it reshape it to 1-Dimensional to make it feature vector for training. So, our feature vector of dimension 2160X1 is ready for training using Artificial Neural Network. Create same feature vector for all training images.

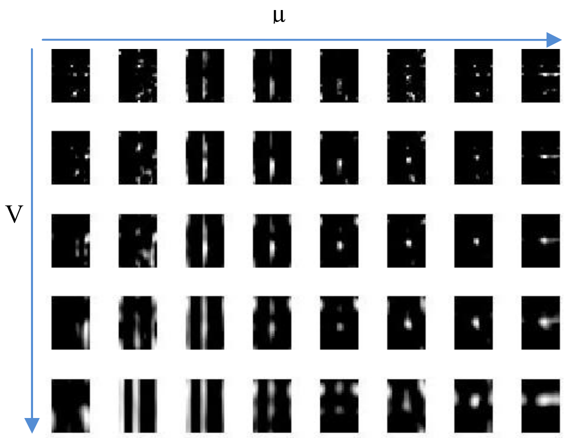


Figure 5 Normalized Featured Images of 1 Edited Image.

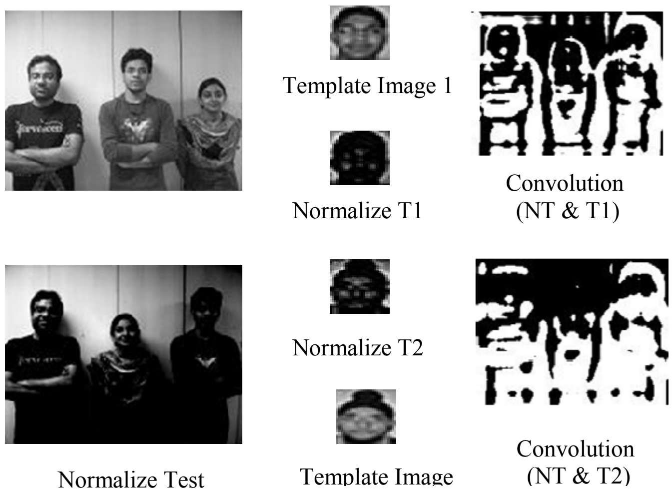


Figure 6 Results after Convolution between Normalize Test Image and Template Image T1&T2.

VI. TRAINING USING ANN

Now, assign the desired output -0.9 to non-face feature vector and 0.9 to face feature vector these will be the network desired output, face and non-face feature as the input of network. After that we have trained our data using artificial neural network for 400 iterations or fixed goal 0.0001, from both those achieving training first will stop and trained data will be stored for testing purpose.

VII. TESTING OF FACE DETECTION

In testing phase, our main emphasis is on detecting all the face as much as possible in immediate time. So, first our RGB test image should be converted into grayscale level and after that finding region in the test image where the possibility of getting a face is high. To find the possible regions where face will be found follow the following steps:

STEP 1: Normalize the test image using equation (4).

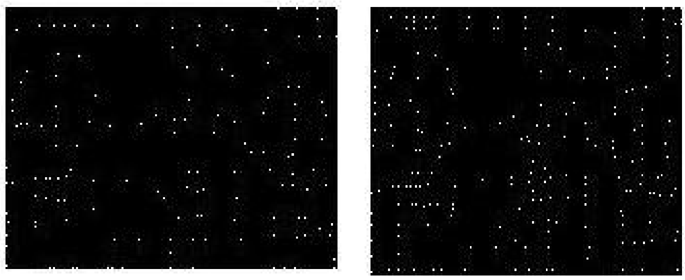
STEP 2: Take two image of face image from database as template image let say T1 and T2, and normalize it using equation (4).

STEP 3: Apply 2D Convolution between test image and template image T1 and T2, see the result in Figure 6.

STEP 4: Find the regions where maximum value in both convoluted images using 8 connected regions where maximum region found set it to 1 and all other regions set to 0 as shown in Figure 7.

STEP 5: Combine the maximum region found in two images in single one image as shown in Figure 8. Here we have found the possible positions where face will be found.

In Figure 8 (b) yellow part point shows the possible region where face found, the difference between Figure 8 (a) and Figure 8 (b) is that in Figure 8 (b) the few upper row pixel value and few lower row pixel values is not marked to detect the face.



(a) (b)

Figure 7 Result after max region set to 1 and other to 0, (a) First convoluted image, (b) Second convoluted image.

For matching the face feature follow the following steps:

STEP 1: Pick up the first yellow point pixel position present in Figure 8(b) and set this pixel normal.

STEP 2: Consider the pixel as a centre and cut an image of size 27X18 from the test image.

STEP 3: Extract the Feature From the cut image by the method describes in section V and simulates the artificial neural network giving the trained data and test feature vector as input.

STEP 4: (I) If the OUTPUT is less than -0.95 then the centered pixel surrounding 7X7 pixels set to normal value and update the image of Figure 8 (b) and Go to STEP1 else continue.

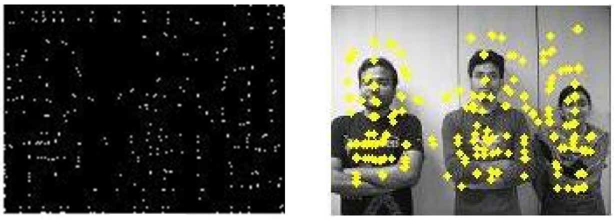
(II) If the OUTPUT is less than -0.5 go to STEP1 else continue.
(III) If the OUTPUT is greater than 0.95 than update the 27X18 surrounding pixel value to normal one and go to STEP5

(IV) If the OUTPUT is less than 0.5 or greater than 0.5 and go to STEP5

STEP 5: Check the surrounding three pixels and cut the image of 27X18 as consider its centre and do as STEP3. If OUPUT >0.95 set all 27X18 pixel to normal one.

STEP 6: If OUTPUT >0.5 than in image Figure 8 (a) set there corresponding pixel to 1. Repeat STEP 1 to STEP 6 until all yellow pixels will not be normal.

Output after completing this process is shown in Figure 9 and from that we have find the centroids of all detected face image and cropped it from the test image as shown in Figure 10.



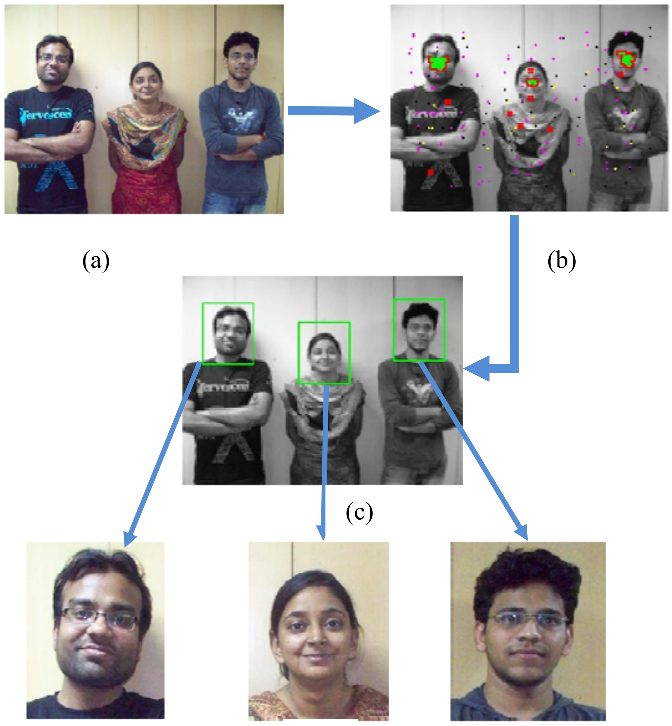
(a) (b)

Figure 8 In Final Image White and Yellow dot shows possible region where face found.

Figure 9 Image after follow all the steps of Face Matching Feature.

VIII. EXPERIMENT AND RESULT ANALYSIS

We tested face detection technique on the basis of parameter of Gabor Wavelet Filter.
The parameter value proposed by Lades and et al. [5], does not giving satisfactory result for our database. So, we have tested it with different parameter and conclude the parameter value used for detection of face in our work.



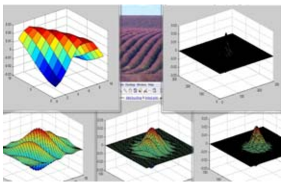
(a) (b) (c) (d)

Figure 10 Face Detection in an image (a) Test image (b) Matched face features in Test image (c) Detected face in test image (d) Cropped faces from Test image.

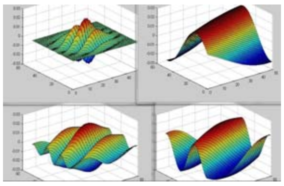
VIII.I EFFECTS OF PARAMETER ON GABOR WAVELET FILTER

For creation of Gabor wavelet filter six parameter are required, parameters are Gabor window size, scaling factor V, orientation μ, maximum frequency K_{max}, sigma σ width of Gaussian kernel and f spacing factor between two Gaussian kernels in frequency domain. We tested every parameter effect individually on Gabor filter by keeping other parameter constant. We created of Gabor filter with the value of parameters are window size of 32X32, five different scales $V \in \{0 \dots 4\}$, eight different orientation $\mu \in \{0 \dots 7\}$, $\sigma = \pi$, kmax = π and f = sqrt(2).
At firstly, varied the window size of Gabor to24x24, 40X40, and 50X50, it refers to closeness of lobe to centre as shown in Figure 11(a), starting from top-left anticlockwise direction. Increase in maximum frequency Kmax reduced the number of rotation as shown in Figure 11(b), starting from top-left anticlockwise direction. As the scaling factor decreases the spread is getting reduced as shown in Figure 11 (c), starting from anticlockwise directions. The sigma is the width of the lobe, as it increases the thickness is increases accordingly as shown in Figure 11(d), starting from left topmost in anticlockwise direction.

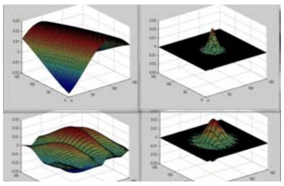
The spacing factor between two Gaussian kernels obviously increasing as shown in Figure 11(e), starting from anticlockwise directions. Increase in orientation is to rotate the lobe.



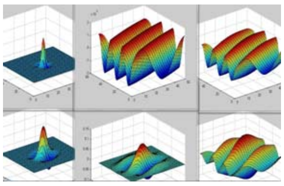
(a)



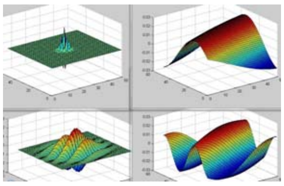
(b)



(c)



(d)



(e)

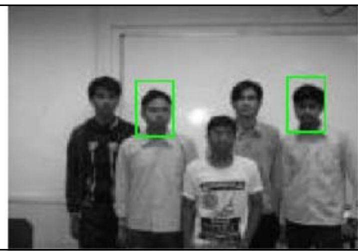
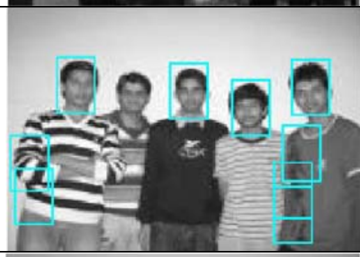
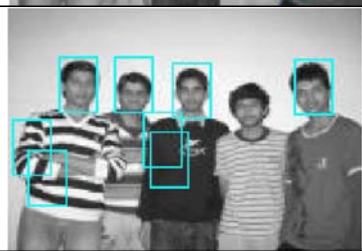
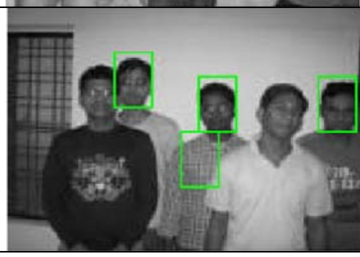
Figure 12 Effect of parameter on Gabor Filter, (a) Window size effect, (b) Kmax effect, (c) Scaling effect, (d) Sigma effect, (e) f spacing factor effect.

VIII.II EFFECTS OF PARAMETER CHANGES ON FACE DETECTION

We have tested the images by varying the Gabor Filter parameter and the results are shown in Table 1.

We have got the best result using the parameter value are, window size 32x32, five different scales V□ {0 . . . 4}, eight different orientation μ □ {0 . . . 7}, σ = π, kmax = π and f = sqrt(2) as shown in Figure 12.

Table 1 Result of face detection after varying the parameter of Gabor Filter

Test case	**Parameter**	**Result**
1.	σ= π/2 and Kmax=2* π	
2.	Window size 24x24	
3.	Scale =[0:4]+2	
4.	σ= π*0.3 and Kmax=1.5* π	
5.	Window size 50x50	

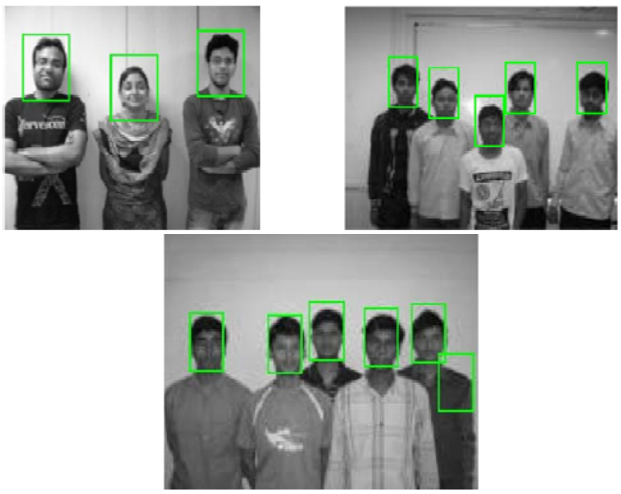


Figure 12 Best results obtained using proposed parameter value.

IX. CONCLUSION

On the basis of result we came to conclusion that parameters of Gabor filters plays an important role in face detection and we can vary only few parameter on the basis of the normal, far and near cases. The conclusions are as follows:

Distance of the face from the camera plays an important role in face detection. The pixel size of the face is generally small when the face is generally at large distance and therefore it is under-sampled while the face which is closed occupies larger pixel area and therefore being oversampled has greater chance of detection. Increase in scaling prefers near Images and vice versa.

The Orientation of Gabor wavelet filter is responsible for different angle edges.

The value of sigma and maximum frequency parameter in Gabor wavelet filter is very sensitive for the type of features. Any deviation in these two decreases the performance. Therefore we have fixed these values of sigma=pi, freq=pi.

The Variable window size helps but does not ensures detection of all faces in image. Effects of parameter changes on face detection have been done.

X. REFERENCES

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