Edge Based Models for Face Recognition

Chapter 4

Edge Based Face Recognition Models

4.1. Introduction

Extraction of edges from an image for analyzing and understanding of the image is a fundamental task in computer vision applications Edges are skeleton of an image structure with significant information content and hence are important feature points in image matching, shape description etc (Suzuki Y, Shibata T, 1982) Edges are used to locate significant variations of gray images and hence useful to provide meaningful description for objects under inspection The edge representation of an image drastically reduces the amount of data to be processed, yet it retains the important information about the structure of objects in the scene This is a process which is carried out effortlessly by the human vision system, but when vision algorithms are designed to mimic this action, quite a few problems such as edge localization, true edge pixels' extraction may be

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* Some parts of the material in this chapter appeared in the following research papers

1 **An Edge based Model for Efficient Representation and Accurate Recognition of faces** International Journal of Multi-disciplinary Research in Advances of Engineering, Vol 3, No III, July 2011 http //jww jscent-journals com

2 **A Rule based Model for Efficient Representation and Accurate Recognition of Human Faces**, IEEE –International Conference on Advances in Computer Engineering (ACE), 2010 (Indexed), pp 326-329- 978-0-7695-4058-0/10 © 2010

encountered The recognition of a face image is based on the existence of some physical features or components since such components together with their relative positions form a representation of the whole face Thus, the recognition of a face involves finding out, first, the edge components of the face and then the study of characteristic features existing among them In view of this, we are motivated to obtain an edge (skeleton) image of a face and then to compute representative feature value based on some defined rules Hence the approach is also called rule based face recognition approach The approach is based on the structure and topology of edges and hence it is also called as edge based face recognition

Edges provide rich information and serve as practical descriptive primitives for face recognition (Leung, 1998) Gao (2002) used edges to recognize faces Hence, the motivation is towards exploring whether edges with their spatial structure can recognize face images Thus in this work, some novel methods of recognizing faces by considering characteristic properties of edges viz, *straightness and crookedness* has been experimented

In this chapter, we propose novel approach for recognizing a face based on the edge topology The proposed model has two stages viz, training and recognition which works as follows The proposed model works by deriving rules using edge features extracted using any edge detector and assume that the number of classes is fixed and known Based on the characteristics of edges, the rules are derived for each class In the first phase, two specific characteristics of the edges viz straightness and crookedness are identified These characteristics depend upon factors such as *centroid, aspect ratio, compactness* and *distance* In the second phase, rules are derived to generate knowledge base, which is subsequently used for recognition purpose During training, a representative feature value is calculated for each class based on the average percentage of edges that satisfy the rule In recognition, the representative feature value of an unknown face image is compared against the class representative feature value to assign a label to it

4.2. Related Works

In the literature, to the best of our knowledge, there is hardly any reported research work on face recognition using edge curves of faces except the outlines of face profiles The only most related work was done by TakaÂcs (1998) using binary image metrics Directional edge-based image feature representations have been developed and applied to medical radiograph analysis, face detection, and face identification The scheme of the feature-vector generation is considered as a dimensionality reduction from a high-dimension edge feature map space to a low-dimension edge histogram space Suzuki and Shibata (2007) proposed the method for validating the directional edge-based feature representations by employing the hierarchical clustering based on the spatial correlations of edges In their study, the feature representations of images have been evaluated using facial images as the test vehicle As a result, the validity of using the directional edge-based feature vectors in image recognition has been verified by the similarity between the results of the hierarchical clustering and the schemes employed in the feature representations

The Line Edge Map (LEM) is proposed by Gao (2002) to integrate the structural information with spatial information of a face image by grouping pixels of face edge map to line segments After thinning the edge map, a polygonal line fitting process (Leung and Yang 1998) was applied to generate the LEM of a face An example of a human frontal face LEM is illustrated in Fig 4 1

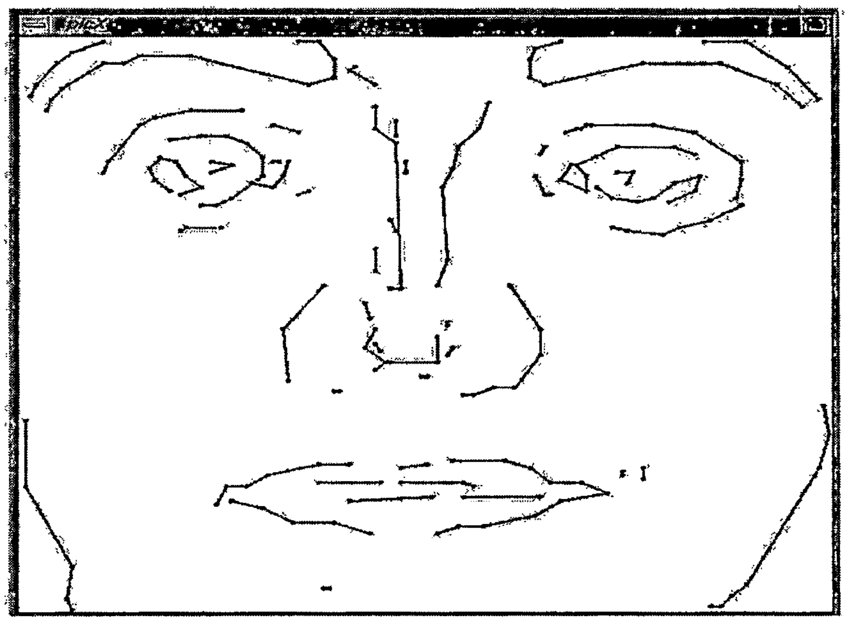


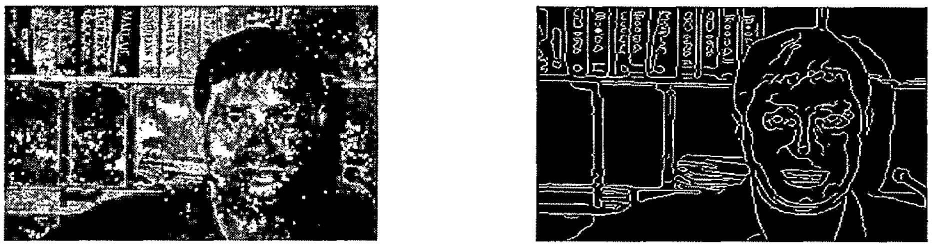
Fig 4 1 An illustration of a face LEM

The LEM representation, which records only the end points of line segments on curves, further reduces the storage requirement Efficient coding of faces is a very important aspect in a face recognition system LEM is also less sensitive to illumination changes due to the fact that it is an intermediate-level image representation derived from low level edge map representation The basic unit of LEM is the line segment grouped from pixels of edge map In this method, Gao et al (2002) explore the information of LEM and investigate the feasibility and efficiency of face recognition using LEM A novel Line Segment Hausdorff Distance (LHD) measure is then proposed to match LEMs of faces The LHD has better distinctive power because it can make use of the additional structural attributes of line orientation, line-point association, and number disparity in LEM, i e , it is not encouraged to match two lines with large orientation difference, and all the points on one line have to be matched to points on another line only

4.3. Edge Detection

As edges play a dominant role in machine vision applications, the continued development of edge detectors is producing increasingly complex edge detection algorithms Based on the behavioral study of the edges with respect to the differentiation operator, these models are broadly classified into five categories viz , Gradient edge detector (Sobel, 1970, Prewitt, 1970, Nevatia and Babu, 1980), Zero-crossing (Haralick, 1984), Laplacian of Gaussian (Marr and Hildreth, 1980), Gaussian edge detectors (Canny, 1986, Deriche, 1987, Sarkar and Boyer, 1991) and Colored edge detectors (Garcia et al 1999) The most widely used among gradient edge detector based algorithms is Nevatia and Babu (1980) technique which consists of determining the edge magnitude and direction by convolving the image with a number of masks followed by thinning and thresholding edge magnitudes Haralick (1984) proposed zero crossing approach which uses second directional derivative and includes Laplacian operator Marr and Hildreth (1980) proposed an edge detector which combines Gaussian filtering with the Laplacian The methods that convolve the image with the derivative of Gaussian are called Gaussian edge detectors Among these Gaussian edge detectors, Canny edge detector (1986) is being widely used in most of the applications This algorithm is suitable especially in noise conditions Deriche (1987) extended Canny's initial filter to two dimensions, Shen and Castan (1992) derived an exponential filter and implemented it using recursive filtering Sarkar and Boyer (1991) propose an optimal infinite-response edge detection filter using an ideal step edge and Canny's criteria

On contrary to the models that are based on the differential operators using single scale information, there exists another class of edge detection techniques that fuse the multi-scale edge information of an image to obtain a robust edge map (Gunsel, 1994, Lu and Jain, 1992, Sun et al 2004) As the wavelet transform is a better tool which can provide multi-scale information of an image and has good time frequency characteristics, many techniques have been developed using the wavelet transform for the purpose of edge detection



(a)Face image without cropping (b) Canny edges

Fig 4 2 Face image and its Canny edges

The Fig 4 2 (a) shows the face image without cropping, i e , with the varied background which is real time practical scenario in uncontrolled environments Fig 4 2 (b) depicts the canny edges of the given face image

4.4. Proposed Methodology

The proposed model works on edges extracted using any suitable edge detector Similar to LDA, here we assume that the number of classes is fixed and known Based on the characteristics of edges, the rules are derived for each class The proposed model that works on the rules for recognition of face images consists of (i) edge feature extraction and (ii) representative feature value generation based on rules In the first phase, two specific characteristics of the edges namely *straightness* and *crookedness* are extracted These characteristics depend on whether the centroid of an edge falls on it or outside In the second phase, rule based system is introduced to extract feature values subsequently for recognition purpose The following sub section details these two phases

4.4.1. Edge features to derive rules

The edges are detected using the Canny edge detector and edges containing less than four pixels are eliminated since they are too small to be labeled as straight or crooked The *straightness* or *crookedness* of an edge is characterized by considering the centroid, distance, compactness and aspect ratio properties

Centroid based straightness For each edge, the centroid (C_x, C_y) is computed, given by $C_x = \frac{1}{n}\sum_{i=1}^{n} x_i$ and $C_y = \frac{1}{n}\sum_{i=1}^{n} y_i$ where {x_1, x_2 x_n} and {y_1, y_2 y_n} be the sets of X and Y co-ordinates of edge pixels Using this definition of centroid, the straightness of an edge is defined as

$$Cent\_Edge = \begin{cases} 1, & (C_x \in X) \cap (C_y \in Y) \\ 0, & otherwise \end{cases} \quad (4\ 1)$$

That is, if centroid of the edge falls on its edge then the method considers that the edge possess straightness property (*Cent_Edge =1*) If the centroid does not falls on its edge, the edge is said to be crooked (*Cent_Edge = 0*) In order to improve the robustness of determining the straightness of an edge, it is further divided into two sub-edges at the estimated centroid The straightness property of the two sub-edges SP_1 and SP_2 are again checked using Eq (4 1) If the two sub-edges satisfy the condition of straightness then the sub-edge is labeled as straight We use the notation *Cent_SP₁* and *Cent_SP₂* to define the straightness of sub-edges SP_1 and SP_2

Distance based straightness The straightness of edge is also estimated using the distance between the two end points of an edge and the number of pixels in the edge Let (x_1, y_1) and (x_2, y_2) be the coordinates of an edge and S_E be the number of pixels in an edge The straightness, St_Edge, is defined as $\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} / S\_E$ If the edge satisfies the condition (St_Edge = 1) then the edge is considered as straight edge else it is considered as cursive edge (St_Edge = 0)

Compactness based straightness of the edge is estimated as follows Let L_E and W_E be the length and width of an edge and it is defined as the difference between the x-coordinates and y-coordinates of the end points of an edge. Straightness of an edge, say Comp_Edge, is defined as the ratio between the perimeter of the edge to its area, and it is computed as L_E * W_E If the edge satisfies the condition (Comp_Edge = 1) then the edge is considered as straight edge else it is considered as cursive edge (Comp_Edge =

0) Further, edge straightness properties are computed by dividing the edge into equal sub parts namely $Part_1$_Edge and $Part_2$_Edge when the edge does not satisfies the above condition If $Part_1$_Edge satisfies the specified condition, then it is considered as straight edge ($Part_1$_Edge = 1) else it is considered as cursive edge ($Part_1$_Edge = 0) Similarly, if $Part_2$_Edge satisfies the condition stated above, it is considered as straight edge ($Part_2$_Edge = 1) else it is considered as cursive edge (Part2_Edge = 0)

Aspect ratio based straightness and cursive property: Here, the aspect ratio, Ar_St, of edges is computed which is defined as the ratio between the length (LE) and width (WE) of the edges The straightness and cursiveness based on aspect ratio is shown in Eq (4 3) to Eq (4 6)

$$Ar\_Edge = \begin{cases} 1, & Ar\_St = 1 \\ 0, & otherwise \end{cases} \quad (4\ 2)$$

That is, if the edge satisfies the condition Eq (4 2) then it is straight edge (Ar_Edge = 1), otherwise it is considered as cursive edge (Ar_Edge = 0) Further, similar to the above, an edge is divided into two segments and checked for its straightness on the sub-segments Ar_1_Edge and Ar_2_Edge, using aspect ratio concept

Similarly, we proposed to compute Arl_St defined as the ratio between the number of pixels (LP) and width (WE) of an edge The straightness property of an edge is defined below

$$Arl\_Edge = \begin{cases} 1, & Arl\_St > 1 \\ 0, & otherwise \end{cases} \quad (4\ 3)$$

If the edge satisfies the equation (4 3) then it is considered as one edge property (Arl_Edge = 1), say EP_1, else it is (Arl_Edge = 0), say EP_2 The vertical edge, V_Edge, defined by

$$V\_Edge = \begin{cases} 1, & (LE > WE) \\ 0, & otherwise \end{cases} \quad (4\ 4)$$

If the edge satisfies the equation (4 4) then it is considered as vertical edges (V_Edge=1) otherwise it is considered as horizontal edges (V_Edge = 0)

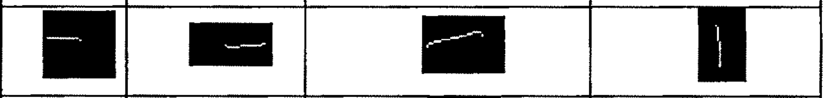
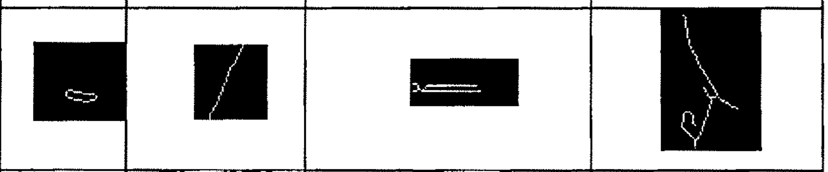
4.4.2. Rules to generate representative

In this sub section, we present seventeen distinct rules, the combination of which we used for generating representative feature value for each class Rules are derived based on the edge properties as described in the previous section The rules are shown in Table 4 1

Table 4 1 Rules to generate representative

R_1= (V_Edge=0) & (Cent_Edge=1) & (Cent_SP_1=1) & (Cent_SP_2 = 0)	R_2= (Cent_Edge=1)&(Cent_SP_1=1) & (Cent_SP_2=1)
R_3 = (Cent_Edge=1) & (Cent_SP_2=1)	R_4=(V_Edge=0),
R_5= (Comp_Edge=0)	R_6=($Part_2$_Edge=0)
R_7= (Arl_Edge=1)	R_8 = (St_Edge=0)
R_9 = (Ar_Edge=0)	R_{10}=(Comp_Edge=0) & ($Part_1$_Edge=0)&($Part_2$_Edge=0)
R_{11}=(Comp_Edge=0)&($Part_1$_Edge=0)	R_{12} = (Cent_Edge=1) & (Cent_SP_1=0)
R_{13}= (V_Edge=1) & (Cent_Edge=1) & (Cent_SP_2=1),	R_{14}= (Ar_1- - edge) = 0
R_{15}=(V_Edge=0)&(Comp_Edge=0 & ($Part_1$_Edge=0)	R_{16} = (V_Edge=0) & (Ar_2_Edge=1)
R_{17}= (V_Edge=0) & (Cent_Edge=1) & (Cent_SP_1=0)	

Table 4 2 Sample edges of rules for face with cropping on CALTECH face database

Rule	Face class	Example Edges
R_1	F15	
R_2	F10	
R_3	F2	
R_4	F6	
R_9	F11	
R_{15}	F8	
R_{17}	F9	

4.4.3. Class Representative

In the previous sub section, we have presented rules for deciding the class representatives based on edge properties Here, we present the procedure to generate the percentage of edges that represent the class As mentioned earlier, the percentage of edges (P_c) in an image that satisfy the rule corresponding to a particular class is first calculated as $P_c = (E_c / E) * 100$, where E_c is the number of edges that satisfy the rule and E is the total number of edges The class representative R_c is calculated as $R_c = \frac{1}{N_c} \sum P_c$ Here N_c is the number of images in the training set for class c

Experimental Analysis on CALTECH Face Databases:

Classification of CALTECH face database is not as easy as classifying other face databases since it contains more number of classes and more number of images with varying background and illumination As a result, it is difficult to find rules for all 26 classes Therefore, we have divided the whole 26 face classes into two subgroups at first level Recursive division is employed until we obtain desired number of classes so that classification can be achieved with proposed seventeen rules only A simple heuristic rule has been employed to classify 26 classes into two groups which is based on the maximum and minimum representative feature value associated with rule R_4

The following experimental set up has been made to demonstrate the feasibility of the proposed model The CALTECH face database is subjected to experimentation with cropping and also without cropping Using rule R_4, two clusters of classes have been obtained for both cropped and un-cropped database Representative feature value for each class is shown in Table 4 3 and Table 4 4

Table 4 3 Representatives of Group 1 (G1) for 100%, 75% and 25% Training images (No Cropping)

No	F-Class	Images	Rules	Rep-100	Images-75	Rep-75	Images-25	Rep-25
1	F-5	22	R_{13}	19 24	16	19 23	6	18 17
2	F-6	24	R_4	34 60	18	35 00	6	35 55
3	F-7	21	R_{16}	0 00	15	0 00	5	0 00
4	F-9	22	R_{17}	2 89	16	3 12	6	2 63
5	F-11	6	R_{12}	6 96	4	5 95	2	3 13
6	F-13	21	R_{10}	48 60	15	48 63	5	46 90
7	F-18	20	R_7	100	15	100	5	100
8	F-21	21	R_9	94 57	15	94 80	5	94 10
9	F-22	21	R_{11}	60 02	15	59 87	5	62 63
10	F-23	23	R_5	82 70	17	82 67	6	81 92
11	F-24	6	R_6	76 55	4	75 92	2	76 39

Table 4 4 Representatives of Group 2 (G2) for 100%, 75% and 25% Training images (No Cropping)

No	F-Class	Images	Rules	Rep-100	Images-75	Rep-75	Images-25	Rep-25
1	F-1	22	R_{17}	3 80	16	3 58	6	3 09
2	F-2	21	R_3	30 41	15	31 01	5	31 92
3	F-3	6	R_9	94 90	4	95 35	2	94 05
4	F-4	23	R_{12}	9 44	17	9 42	6	9 57
5	F-8	6	R_{15}	23 72	4	24 69	2	23 86
6	F-10	8	R_1	1 45	6	1 50	2	1 67
7	F-12	6	R_5	85 35	6	86 43	2	87 71
8	F-14	22	R_{10}	47 26	16	46 66	6	46 93
9	F-15	26	R_{11}	60 20	19	59 89	7	62 00
10	F-16	23	R_6	75 47	17	75 77	6	73 01
11	F-17	6	R_8	99 26	4	99 02	2	98 18
12	F-19	21	R_{16}	0 00	15	0 00	5	0 00
13	F-20	30	R_{13}	17 49	22	16 46	8	18 26
14	F-25	21	R_7	100	15	100	5	100
15	F-26	23	R_{14}	97 16	17	97 29	6	97 42

Similarly, we have obtained representatives of Group-1 (F5, F11, F12, F13, F16, F20, F21, F22), Group-2 (F2, F6, F7, F8, F9, F10, F14, F15, F18, F19, F23, F24, F25, F26) and Group-3 (F1, F3, F4, F17) on cropped face image database

4.5 Experimental Results

This section presents the results of the experiments conducted to corroborate the success of the proposed model We have conducted experimentation on CALTECH face database We have specifically chosen this database as this database contains varying background as well as varying illumination All experiments are performed on a P-IV 2 99GHz Windows machine with 504 MB of RAM

The confusion matrix is presented for different experimental set-up We have considered first 75% of the face images as training samples and the remaining 25% as testing samples and the results are presented in Table 4 5 and Table 4 6 respectively for un-cropped and cropped face database

Table 4 5 Confusion matrix of G1 for 75% training and 25% for testing (No Cropping)

	F-5	F-6	F-7	F-9	F-11	F-13	F-18	F-21	F-22	F-23	F-24
F-5	80 0	40 0	0	0	0	0	0	0	0	0	0
F-6	0	60 0	0	0	0	0	0	0	0	0	0
F-7	0	0	100 0	20 0	0	0	0	0	0	0	0
F-9	0	0	0	80 0	0	0	0	0	0	0	0
F-11	20 0	0	0	0	100 0	0	0	0	0	0	0
F-13	0	0	0	0	0	80 0	0	0	20 0	0	0
F-18	0	0	0	0	0	0	100 0	0	0	0	0
F-21	0	0	0	0	0	0	0	100 0		0	0
F-22	0	0	0	0	0	20 0	0	0	80 0	0	0
F-23	0	0	0	0	0	0	0	0	0	80 0	0
F-24	0	0	0	0	0	0	0	0	0	20 0	100 0

Table 4 6. Confusion matrix of G1 for 75% training and 25% for testing (With Cropping)

	F-5	F-11	F-12	F-13	F-16	F-20	F-21	F-22
F5	100 0	0	0	0	0	0	0	0
F-11	0	100 0	0	0	0	0	0	0
F-12	0	0	100 0	0	0	0	0	0
F-13	0	0	0	100 0	0	0	0	0
F-16	0	0	0	0	100 0	0	0	0
F-20	0	0	0	0	0	100 0	0	0
F-21	0	0	0	0	0	0	100 0	0
F-22	0	0	0	0	0	0	0	100 0

Similarly, we have considered first 25% of the face images as training samples and the remaining 75% as testing samples and the results are presented in Table 4 7 and Table 4 8 respectively for un-cropped and cropped face database

Table 4 7 Confusion matrix of G1 for 25% training and 75% for testing (No cropping)

Face Class	F-5	F-6	F-7	F-9	F-11	F-13	F-18	F-21	F-22	F-23	F-24
F-5	93 3	17 6	0	0	0	0	0	0	0	0	0
F-6	6 6	64 7	0	0	0	0	0	0	0	0	0
F-7	0	0	100 0	6 6	0	0	0	0	0	0	0
F-9	0	0	0	40 0	0	0	0	0	0	0	0
F-11	0	0	0	53 3	100 0	0	0	0	0	0	0
F-13	0	17 6	0	0	0	93 3	0	0	13 3	0	0
F-18	0	0	0	0	0	0	100 0	13 3	0	0	0
F-21	0	0	0	0	0	6 6	0	86 6	0	12 5	0
F-22	0	0	0	0	0	0	0	0	86 6	0	0
F-23	0	0	0	0	0	0	0	0	0	75 0	0
F-24	0	0	0	0	0	0	0	0	0	12 5	100 0

Table 4 8 Confusion matrix of G1 for 25% training and 75% for testing (With Cropping)

Face Class	F-5	F-11	F-12	F-13	F-16	F-20	F-21	F-22
F-5	100 0	0	0	0	0	0	0	0
F-11	0	100 0	0	0	0	0	0	0
F-12	0	0	100 0	0	0	0	0	0
F-13	0	0	0	100 0	0	0	0	6 6
F-16	0	0	0	0	100 0	0	0	0
F-20	0	0	0	0	0	100 0	0	0
F-21	0	0	0	0	0	0	100 0	0
F-22	0	0	0	0	0	0	0	93 3

The overall accuracy is given in Table 4 9

Table 4 9 Performance of the method for CALTECH database (Cropped and non-cropped data)

No of Training	No of Testing	Accuracy-Non crop	Accuracy-Crop
445	445	83 8%	87 8%
341	104	79 2%	90 7%
123	322	80 0%	88 9%

In order to reveal the *superiority of the proposed rule based model, Eigenfaces based model is considered for comparative study* The obtained confusion matrix for Group-1 with the same experimental set-up is shown in Table 4 10 and Table 4 11 The results are presented only for cropped face databases

Table 4 10. Confusion matrix of G1 for 75% training and 25% for testing (With Cropping)

	F-5	F-11	F-12	F-13	F-16	F-20	F-21	F-22
F5	100 0	0	0	0	0	0	0	0
F-11	0	100 0	0	0	0	0	0	0
F-12	0	0	100 0	0	0	0	0	0
F-13	0	0	0	100 0	0	0	0	0
F-16	0	0	0	0	100 0	0	0	0
F-20	0	0	0	0	14 28	85 72	0	0
F-21	0	0	0	0	0	0	100 0	0
F-22	0	0	0	0	0	0	0	100 0

Table 4 11 Confusion matrix of G1 for 25% training and 75% for testing (No Cropping)

	F-5	F-11	F-12	F-13	F-16	F-20	F-21	F-22
F5	93 33	0	0	0	6 66	0	0	0
F-11	0	66 66	0	0	33 3	0	0	0
F-12	0	0	33 33	0	66 66	0	0	0
F-13	6 66	0	0	80 54	13	0	0	0
F-16	0	0	0	0	100 0	0	0	0
F-20	0	0	0	0	0	100 0	0	0
F-21	0	0	0	0	0	0	100 0	0
F-22	6 66	0	0	0	0	0	6 66	86 6

4.6 Conclusion

We made successful attempt to explore the applicability of rule based method for face recognition We understand that almost all works related face recognition relies on statistical/mathematical or structural approaches To the best of our knowledge, the rule based concept is very rarely used in literature In our work, we have considered CALTECH database for experimentation, which has varied background/illumination The Eigenface technique is considered for comparative study The overall contributions can be summarized as follows

- A new rule based method for face recognition with fixed and known classes
- The rules are derived from Canny Edge features
- The proposed method is experimented on CALTECH face database which has 450 -face images with varied background, illumination and poses
- The proposed method is experimentally compared with PCA to show its superiority