Chapter-4

FUZZY BASED IMAGE DIMENSIONALITY REDUCTION USING SHAPE PRIMITIVES FOR EFFICIENT FACE RECOGNITION

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4.1 BRIEF OUTLINE OF THE CHAPTER

Human faces are arguably the most extensively studied object in image-based recognition. Today face recognition capability of the human visual system plays a significant role in day to day life due to numerous important applications for automatic face recognition. One of the problems with the recent image classification and recognition approaches are they have to extract features on the entire image and on the large grey level range of the image. To address this, the present chapter proposes an Image Dimensionality Reduction using shape Primitives (IDRSP) model for efficient face recognition. The proposed IDRSP reduces the dimensionality of the image using Shape primitives and reduces the grey level range by using a fuzzy logic while preserving the significant attributes of the texture. Fuzzy logic is applied on IDRSP facial model to reduce the grey level range from 0 to 4. This makes the proposed fuzzy based IDRSP (FIDRSP) model suitable to GLCM. The proposed algorithm consists of four stages. In stage one preprocessing step is adopted to overcome the noise and other effects. In stage two each 3x3 image neighborhood is reduced into 2x2 neighborhood, by using shape primitives. In stage three on the reduced neighborhood a fuzzy logic is applied to reduce the grey level range. In stage four GLCM features are extracted on the proposed model for efficient face recognition.

4.2 METHODOLOGY FOR GENERATING FIDRSP FACE RECOGNITION MODEL

Grey level Co-occurrence Matrices (GLCM) introduced by Haralick [31] attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels. One of the major inconveniences of GLCM is the large range of its possible values (256 gray values) at the same time that these values are not correlated. It also requires more computation time. In general, the size of GLCM depends on gray level range of the image. To address this the proposed FIDRSP model is designed such a way that it will be more suitable to GLCM, because of its overall reduction in image dimension and gray level range. The proposed FIDRSP model with GLCM features combines the merits of both statistical and structural information of images and thus represents complete information of the facial image for recognition of a facial image.

The block diagram of FIDRSP face recognition model is shown in Fig.4.1.

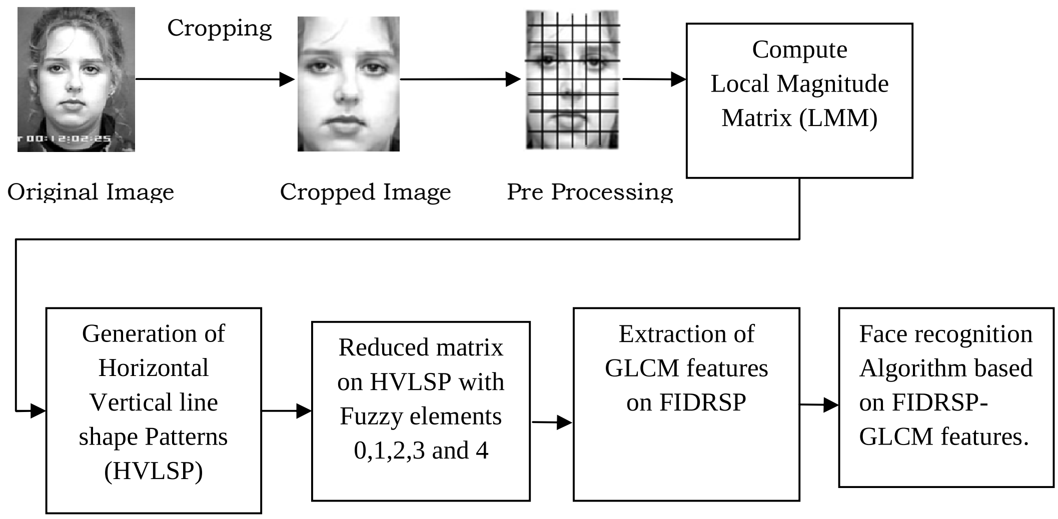


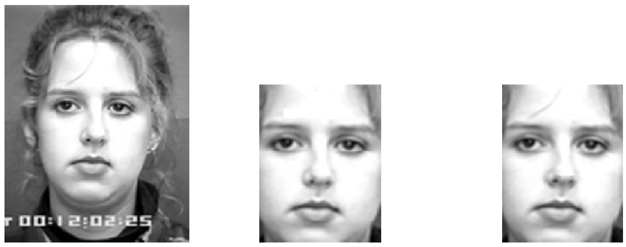
Fig.4.1: Block diagram of FIDRSP face recognition model.

Step 1: In step one the original facial image is cropped. Facial images are cropped from original frames based on the two eyes location. Fig.4.2 shows an example of the original face image and the cropped image.

Step 2: The proposed FIDRSP model adopted a preprocessing method on the cropped image of step 1 to have a better feature representation and feature extraction without any noise and other effects. For this smoothing filter is adopted by the proposed method. This filter reduces the unwanted noise that is present in the cropped image. As a preprocessing step the cropped images are smoothed using 2D Gaussian filter as shown in equation (4.1) along the horizontal and vertical scan lines.

$$G(x, y) = \frac{1}{2\pi\sigma^2}\, e^{\frac{-x^2+y^2}{2\sigma^2}} \qquad (4.1)$$

where ‘x’ is the distance from the origin in the horizontal axis, ‘y’ is the distance from the origin in the vertical axis and ‘σ’ is the standard deviation of the Gaussian distribution.



(a) (b) (c)

Fig.4.2: Preprocessing of face image (a) Original image (b) Cropped image (c) Filtered image.

Step 3: Face Feature Representation using Local Magnitude Matrix: In the third step, Local Magnitude Matrix (LMM) is computed on every 3×3 non-overlapped windows as described below. The LMM gives an efficient representation of face images. Let a neighborhood of 3×3 pixels is denoted by a set containing nine elements: $V = \{V_1, V_2 \ldots V_8, cp\}$, here cp represents the gray value of the centre pixel and $V_1, V_2 \ldots V_8$ represents gray level intensity of neighboring pixels as shown in Fig.4.3(a) The LMM neighborhood pixel are obtained by evaluating the absolute difference between the neighboring pixel and the cp, as described in equation (4.2) and as shown in Fig.4.3(b).

V_1	V_2	V_3
V_4	cp	V_5
V_6	V_7	V_8

(a)

LM_1	LM_2	LM_3
LM_4		LM_5
LM_6	LM_7	LM_8

(b)

Fig.4.3: (a) a 3×3 neighborhood (b) Local magnitude matrix (LMM).

$$\mathrm{LM_i} = \mathrm{abs}(\mathrm{P_i} - \mathrm{cp}) \quad \mathrm{i} = 1,2,\ldots,8 \tag{4.2}$$

Here LM_i represents the local magnitude of the neighboring pixels. equation (4.2) demonstrates that the value of the centre pixel is always '0'.

Step 4: Image Dimensionality Reduction using Shape Primitives (IDRSP) from LMM: The LMM of a 3×3 neighbourhood is reduced into a 2×2 neighbourhood by using "Horizontal and Vertical Line Shape Primitives" (HVLSP). The proposed HVLSP is a connected neighbourhood of three pixels on a 3 x 3 LMM, without central pixel. The HVLSP's on LMM is not considered central pixel because its gray level value is always zero. The average of these HVLSP's generates IDRSP with 2×2 dimension as shown in Fig.4.4 and as represented in equations (4.3) to (4.6).

LM_1	LM_2	LM_3
LM_4		LM_5
LM_6	LM_7	LM_8

(a)

$HVLSP_1$	$HVLSP_2$
$HVLSP_3$	$HVLSP_4$

(b)

Fig.4.4: Construction of IDRSP model (a) LMM of a 3×3 neighbourhood (b) IDRSP matrix obtained from HVLSP's of LMM.

$$\mathrm{HVLSP}_1 = \frac{(\mathrm{LM}_1+\mathrm{LM}_2+\mathrm{LM}_3)}{3} \tag{4.3}$$

$$\mathrm{HVLSP}_2 = \frac{(\mathrm{LM}_1+\mathrm{LM}_4+\mathrm{LM}_6)}{3} \tag{4.4}$$

$$\mathrm{HVLSP}_3 = \frac{(\mathrm{LM}_6+\mathrm{LM}_7+\mathrm{LM}_8)}{3} \tag{4.5}$$

$$\mathrm{HVLSP}_4 = \frac{(\mathrm{LM}_3+\mathrm{LM}_5+\mathrm{LM}_8)}{3} \tag{4.6}$$

Step 5: Reduction of grey level range on IDRSP using fuzzy logic: Fuzzy logic has certain major advantages over traditional Boolean logic when it comes to real world applications such as texture representation of real images. One useful mechanism of reducing grey level range is converting the image grey levels into binary as in the case of LBP, TU and other local approaches. The disadvantages of these approaches are for example if the difference is minimum let us say 1 or maximum i.e. 255, they treat it into 1. That is most of the local approaches treats even the difference ranges from minimum to maximum as homogeneous. This clearly indicates that LBP, TU with non Fuzzy logic information, misuses the power of local approaches. To address these problems Fuzzy Logic (FL) is introduced in the proposed IDRSP model.

In the proposed approach the image grey level values are reduced to the range from 0 to 4 instead of binary '1' or '0'. Though the present FIDRSP model considers five possible fuzzy grey values, but at any time only a maximum of four fuzzy grey levels will appear because there will be four pixels in any 2*2 neighborhood i.e. also in IDRSP model.

The fuzzy membership function is shown in Fig.4.5. The following equation (4.7) is used to determine the fuzzy elements on IDRSP model of 2×2 neighborhood.

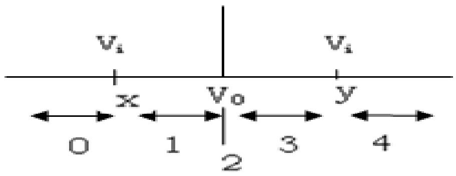


Fig.4.5: Fuzzy membership function representation.

$$\mathrm{FE_i} = \left\{\begin{array}{llll} 0 & \text{if} & \mathrm{HVLSP_i} < avg & \text{and} \quad \mathrm{HVLSP_i} < x \\ 1 & \text{if} & \mathrm{HVLSP_i} < avg & \text{and} \quad \mathrm{HVLSP_i} > \mathrm{x} \\ 2 & \text{if} & \mathrm{HVLSP_i} = \mathrm{avg} & \\ 3 & \text{if} & \mathrm{HVLSP_i} > avg & \text{and} \quad \mathrm{HVLSP_i} > y \\ 4 & \text{if} & \mathrm{HVLSP_i} > avg & \text{and} \quad \mathrm{HVLSP_i} < y \end{array}\right\} \quad \text{for i} = 1,2,3,4. \quad (4.7)$$

Where x, y are the user specified values, avg represents the average of the IDRSP model of 2×2 neighborhood.

7	5
1	3

(a)

4	3
0	1

(b)

Fig.4.6: The process of evaluating Fuzzy IDRSP model (a) sample IDRSP model (b) FIDRSP model.

The proposed FIDRSP model using HVLSP reduces the 3×3 neighbourhood in to a 2 x 2 and also it reduces the grey level range into 0 to 4 values. This reduction is based on the assumption that the face image classification is a data generalization process and reducing the image and grey level data variability to some extent should not seriously influence the classification accuracy. According to Narayanan et al. [52], reducing data down to 4 bits from 8 bits would still preserve more than 90 percent of the texture information content.

Step 6: Evaluation of GLCM features on FIDRSP model of the image: Haralick has defined a total of 14 features on GLCM. The advantage of the proposed FIDRSP-GLCM scheme is that it has used only four features for effective face recognition. The features are Contrast, Energy, Local homogeneity and correlation represented from equations (4.8) to (4.11) respectively.

$$\text{contrast} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \tag{4.8}$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \tag{4.9}$$

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1 + (i - j)^2} \tag{4.10}$$

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i - \mu)(j - \mu)}{\sigma^2} \tag{4.11}$$

Where P_{ij} is pixel intensity value at (i, j), μ is mean and σ varience.

4.3. RESULTS AND DISCUSSIONS

The proposed FIDRSP model with GLCM features is applied for accurate recognition of human faces. The proposed FIDRSP model is experimented with a database of the 1002 facial images collected from FG-NET database and other 600 images collected from the scanned photographs. This leads a total of 1602 sample facial images. Sample images of each group images are shown in Fig.1.4.

The features of GLCM contrast, correlation, energy and local homogeneity are extracted on FIDRSP model of different facial images and the results are stored in the feature vector. Feature set leads to representation of the training images. Table 4.1 represents the derived four features on GLCM on 56 facial images. The facial recognition algorithm on the proposed FIDRSP model is represented in algorithm 4.1.

Table 4.1: GLCM feature set values on FIDRSP model facial images.

S. No.	Image name	Contrast	Correlation	Energy	Local Homogeneity
1	001A02	5.06013	0.1046635	0.7920564	0.909640460
2	001A08	5.13860	0.1147774	0.7876613	0.908239197
3	001A14	6.85826	0.1101393	0.7223374	0.877531000
4	001A43a	5.45958	0.0957195	0.7777805	0.902507456
5	001A22	4.24549	0.0902282	0.8256290	0.924187726
6	002A05	5.78490	0.0469167	0.7720083	0.896698255
7	001A16	5.27106	0.0485252	0.7909407	0.905873947
8	002A31	4.77828	0.0601755	0.8082341	0.914673586
9	002A29	6.23240	0.0955032	0.7483644	0.888707130
10	002A12	5.43163	0.0759139	0.7814822	0.903006543
11	002A03	6.92354	0.1103415	0.7198466	0.876365284
12	002A05	6.29709	0.0779239	0.7486308	0.887551926
13	004A19	6.33484	0.0817687	0.7466365	0.886877832
14	004A21	6.38258	0.1056107	0.7410726	0.886025302

15	003A58	6.60982	0.1074603	0.7321671	0.881967523
16	004A26	7.13350	0.1052307	0.7129096	0.872616125
17	004A48	6.50464	0.0994927	0.7374598	0.883845721
18	002A15	6.80372	0.0993711	0.7262568	0.878505068
19	004A53	6.86221	0.1059765	0.7229217	0.877460586
20	004A63	6.41194	0.1233346	0.7370020	0.885501126
21	005A49	5.52721	0.0546365	0.7806042	0.901299737
22	002A38	5.90649	0.0977586	0.7603884	0.894527027
23	005A52	6.15246	0.0969369	0.7511667	0.890134587
24	004A28	6.19691	0.1160354	0.7464580	0.889340892
25	005A61	6.77544	0.1113417	0.7252465	0.879009956
26	006A24	5.50491	0.0958337	0.7760236	0.901698009
27	006A28	5.60465	0.0801154	0.7743603	0.899917035
28	006A31	5.57827	0.0826049	0.7750250	0.900388090
29	006A67	6.77472	0.0895310	0.7290008	0.879022861
30	006A46	5.79544	0.1079085	0.7631337	0.896509956

31	006A55	5.78135	0.0956982	0.7654615	0.896761615
32	007A45	6.29086	0.1166909	0.7427524	0.887663164
33	008A03	6.13837	0.1130926	0.7491737	0.890386246
34	008A06	6.12681	0.1149200	0.7493256	0.890592736
35	008A12	6.46721	0.0983979	0.7390479	0.884514196
36	008A13	6.03936	0.1146154	0.7527315	0.892154314
37	008A16	5.69860	0.1016087	0.7677761	0.898239307
38	009A11	6.36422	0.1227412	0.7389330	0.886353245
39	009A13	5.03045	0.0914944	0.7948762	0.910170538
40	009A01	4.90217	0.0669688	0.8027397	0.912461283
41	008A17	5.92481	0.1087734	0.7580339	0.894199853
42	008A31	5.87241	0.1023483	0.7610082	0.895135509
43	009A05	5.64584	0.1072111	0.7689972	0.899181416
44	009A09	7.34024	0.1167309	0.7030412	0.868924226
45	008A29	7.48081	0.1138514	0.6983540	0.866414086
46	009A09	5.47492	0.1033889	0.7761343	0.902233591

47	009A22a	5.39289	0.0897308	0.7811459	0.903698378
48	009A00	7.00527	0.1212916	0.7147758	0.874905973
49	008A21	5.47600	0.0812628	0.7790943	0.902214233
50	009A01	6.23558	0.1238170	0.7436979	0.888650442
51	008A41	6.83037	0.1332777	0.7192054	0.878029130
52	010A01	4.77642	0.1236211	0.8007962	0.914706858
53	011A07	6.53225	0.1353741	0.7302770	0.883352692
54	011A40	5.96058	0.0952838	0.7586969	0.893561025
55	010A04	5.47673	0.0976771	0.7768536	0.902201327
56	011A42	5.48612	0.0877377	0.7778442	0.902033555

Algorithm 4.1: Face recognition algorithm on FIDRSP model of facial images using GLCM features.

Begin

Input: The test facial Image

Step 1: Convert the given test facial image into FIDRSP model.

Step 2: Evaluate the contrast, correlation, energy and local homogeneity of GLCM features on the proposed FIDRSP model of the test facial images.

Step 3: Find the difference between test facial image features with existing feature vector of the feature library.

Step 4: If difference is zero or falls within the small range then test image is matching with the database image or the test image is recognized.

End

For evaluating successful recognition rate on the proposed FIDRSP model each facial image sample is tested ten times. Each time on each facial image, the four GLCM features on FIDRSP model are evaluated. The ten times evaluated GLCM features on FIDRSP model for the facial images 001A05 and 002A26 are listed in Tables 4.2 and 4.3 respectively. Each time the hit or miss count is measured based on the above novel distance scheme, for all test sample images. The 'hit' indicates the successful recognition with value 'H' and 'miss' indicates an unsuccessful recognition with value 'M'.

The hit or miss count for each time of the facial images 001A08, 001A29, 001A40, 001A19, 004A51, 003A20, 003A35, 004A21, 004A62 and 001A02 from FG-NET aging database and some images from scanned photographs are given in Tables 4.4. Fig. 4.7 and 4.8 indicate the Bar graph for successful recognition of FG-NET aging databases and some images from scanned photographs.

Table 4.2: FIDRSP model-GLCM features of facial image: 001A05 for ten times.

Test No.	Contrast	Correlation	Energy	Local Homogeneity
1	5.43163	0.1046635	0.7920564	0.909640460
2	5.27106	0.1046635	0.7876613	0.896698255
3	5.03045	0.1103415	0.7777805	0.905873947
4	5.13860	0.1233346	0.7720083	0.903006543
5	5.06013	0.1160354	0.7909407	0.886877832
6	5.45958	0.1113417	0.7814822	0.901299737
7	5.47600	0.1079085	0.7806042	0.894527027
8	5.52721	0.1166909	0.7603884	0.889340892
9	5.50491	0.1130926	0.7677761	0.901698009
10	5.47673	0.1146154	0.7948762	0.900388090

Table 4.3: FIDRSP model-GLCM features of facial image: 002A26 for ten times.

Test No.	Contrast	Correlation	Energy	Homogeneity
1	6.86221	0.1059765	0.7229217	0.877460586
2	6.85826	0.1101393	0.7427524	0.881967523
3	6.60982	0.1103415	0.7192054	0.883845721
4	6.38258	0.1056107	0.7390479	0.878505068
5	6.77544	0.1074603	0.7389330	0.877460586
6	7.00527	0.1052307	0.7030412	0.889340892
7	6.83037	0.0994927	0.7147758	0.879009956
8	6.53225	0.0993711	0.7436979	0.874905973
9	6.33484	0.1059765	0.7493256	0.878029130
10	6.80372	0.1233346	0.7302770	0.883352692

Table 4.4: Recognition sequence of the facial images from the FG-NET aging database.

Facial image (001A08)		Facial image (001A29)		Facial image (001A40)		Facial image (001A19)		Facial image (004A51)	
S.no	Hit Miss	S.no	Hit Miss	S.no	Hit Miss	S.no	Hit Miss	S.no	Hit Miss
1	H	1	H	1	H	1	H	1	H
2	H	2	H	2	H	2	H	2	H
3	H	3	H	3	H	3	H	3	H
4	M	4	H	4	H	4	H	4	H
5	H	5	H	5	H	5	H	5	H
6	H	6	H	6	H	6	H	6	H
7	H	7	H	7	H	7	H	7	H
8	H	8	H	8	M	8	H	8	H
9	H	9	H	9	H	9	H	9	H
10	H	10	H	10	H	10	H	10	H

Facial image (003A20)	
S.no	Hit / Miss
1	H
2	H
3	H
4	H
5	H
6	H
7	H
8	H
9	H
10	H

Facial image (003A35)	
S.no	Hit / Miss
1	H
2	H
3	H
4	H
5	M
6	H
7	H
8	H
9	H
10	H

Facial image (004A21)	
S.no	Hit / Miss
1	H
2	M
3	H
4	H
5	H
6	H
7	H
8	H
9	H
10	H

Facial image (004A62)	
S.no	Hit / Miss
1	H
2	H
3	H
4	H
5	H
6	H
7	H
8	H
9	H
10	H

Facial image (001A02)	
S.no	Hit / Miss
1	H
2	H
3	M
4	H
5	H
6	H
7	H
8	H
9	H
10	H

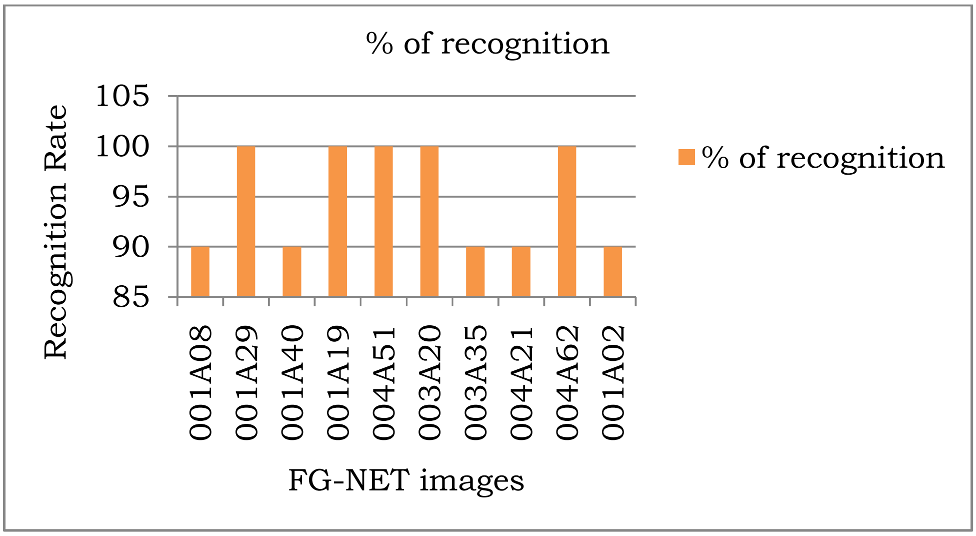


Fig. 4.7: Bar graph for successful recognition rates of FG-NET aging database using FIDRSP model.

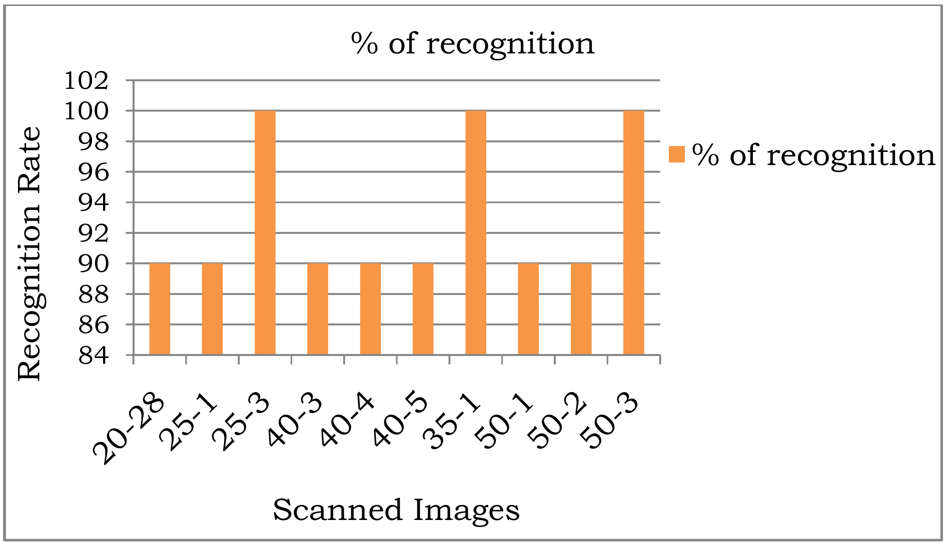


Fig. 4.8: Bar graph for successful recognition rates of Scanned images using FIDRSP model.

From the Table and bar graph it is clearly evident that for FG-NET aging database, the percentage of recognition is 95% and for scanned images 93%.

Table 4.5 shows the recognition rate of faces by the proposed FIDRSP model with GLCM features with other existing methods like Statistical Texture Features (STF) of Dr.V.Vijaya Kumar and M.Chandra Mohan et.al [11] and a novel fuzzy rule base system for faces recognition by Payman Moallema et.al [57], Narayana R.M et.al [52]. From Table 4.5, it is clearly evident that, the proposed FIDRSP model exhibits a high recognition rate than the existing methods. The graphical representation of the percentage mean recognition rate for the proposed FIDRSP model and other existing methods are shown in Fig.4.9.

Table 4.5: The face recognition rate by the proposed and other existing methods.

Image Databse	Statistical Texture Features (STF)	Fuzzy rule for face detection	Proposed FIDRSP model
FG-NET	94	96.7	100
Scanned	93	94	97.5

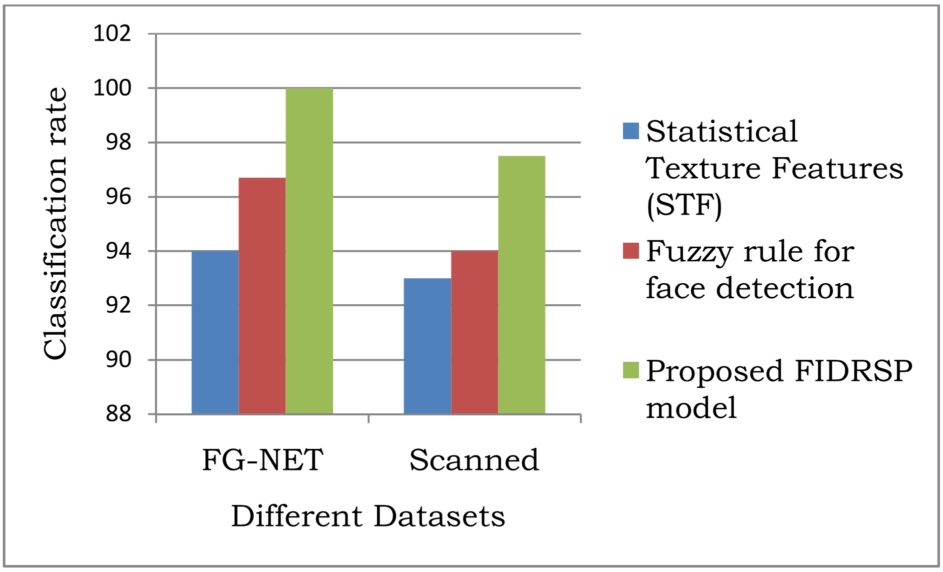


Fig. 4.9: Face recognition chart of the proposed FIDRSP model with GLCM features with other existing methods.

SUMMARY

The proposed Image Dimensionality Reduction using shape Primitives model reduces the overall dimensionality of the image into (2N/3*2M/3), while preserving the significant attributes, local properties and local edge information. Thus the proposed FIDRSP model with GLCM features plays a crucial role in reducing the overall complexity. The derived Fuzzy logic on the proposed FIDRSP model reduced the overall grey level range without any significant loss of local properties and this phenomenon made the proposed method more suitable to evaluate GLCM features. The other advantage of FIDRSP-GLCM features is one need not necessarily to compute all 14 Haralick features to build an efficient face recognition system. The proposed method only by evaluating four features of GLCM on FIDRSP facial model achieved a high class of

recognition rate. The comparison with the existing methods shows the efficacy of the proposed method. The performance of this system is more for the FG-NET aging database than the scanned images. The proposed method can be easily incorporated into surveillance system of police, traffic people, colleges, universities and other public and private places.