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

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Abstract

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. The present paper overcomes this by deriving an approach that reduces the dimensionality of the image using Shape primitives and reducing the grey level range by using a fuzzy logic while preserving the significant attributes of the texture. The present paper proposed an Image Dimensionality Reduction using shape Primitives (IDRSP) model for efficient face recognition. 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 Grey level co-occurrence matrices. The proposed FIDRSP model with GLCM features are compared with existing face recognition algorithm. The results indicate the efficacy of the proposed method.

Keywords:

GLCM Features, Preprocessing, Grey Level Range, Significant Image Features, Dimensionality Reduction

1. INTRODUCTION

Automatic detection of human faces analysis has been the topic of many researches for decades. Human face recognition is also becoming a very important part of many applications, such as video surveillance and security control systems, intelligent human–computer interface, content-based image retrieval, multimedia applications on web like video conferencing, and face database management. A key issue in face analysis is finding efficient descriptors for face appearance. Although this issue is so easy for a man brain, it still remains a challenging and difficult problem for a computer. Difficulties such as differences between various facial expressions, image orientation, presence or absence of structural components (e.g. bread, mustaches and glasses), imaging conditions such as lighting (e.g. spectra, source distribution and intensity), camera characteristics (e.g. sensor and lens response) can be mentioned. Again, occlusion, which means that some faces may be partially occluded by other objects in an image with a group of people, can be a serious problem.

There have been many well-known statistical approaches for face analysis, which include such techniques as principal component analysis [1], linear discriminate analysis [2], independent component analysis (ICA) [3] and support vector machine [4]. Recently, local descriptors have gained much attention in the face recognition community for their robustness to illumination and pose variations. One of the local descriptors is local feature analysis (LFA) proposed by Penev et al.[5]. In LFA, a dense set of local-topological fields are developed to extract local features. Through discovering a description of one class objects with the derived local features, LFA is a purely second-order statistic method. Gabor wavelet is a sinusoidal plane wave with particular frequency and orientation, modulated by a Gaussian envelope [6]. It can characterize the spatial structure of an input object, and thus is suitable for extracting local features. Elastic Bunch Graph Matching (EBGM) [7] represents a face by a topological graph where each node contains a group of Gabor coefficients, known as a jet. The feasibility of the component or patch based face recognition is also investigated in [8], in which the component-based face recognition approaches clearly outperform holistic approaches. However, these methods suffer from the generalization problem due to their robustness to challenges such as pose and illumination changes.

To avoid this problem, non-statistical face analysis method using local binary pattern (LBP) has been proposed.LBP operator is a statistical texture descriptor of the characteristics of the local structure. LBP provides a unified description including both statistical and structural characteristics of a texture patch that is the reason LBP is more powerful for texture analysis. It has been proven that the non-statistical face analysis methods outperform the statistical face analysis methods in terms of recognition performance and the robustness to illumination change [9],[10]. Initially, LBP was first introduced by Ojala et al. [11], which showed a high discriminative power for texture classification due to its invariance to monotonic grey level changes. Recently, Ojala et al. [12] introduced the uniform local binary pattern (ULBP), which extended their original LBP operator to a circular neighborhood of different radius size and selected a small subset of LBP patterns. After that, many variants of LBPs have been introduced by many other researchers and applied to many areas such as face detection [13],[10] face recognition [14],[9],[15],[16], face authentication [17],[18] facial expression recognition [19], gate recognition [20], image retrieval [21], and object detection [22].

However, the original LBP is not efficient because it has a fixed size of feature dimension. In this circumstance, it is observed that certain LBP codes exhibiting transitions from 1 to 0 or 0 to 1 in a circularly defined code are at most two, have been occurred frequently (more than 90%) in the natural images.

Based on this observation, Ojala et al. [12] proposed the uniform LBP (ULBP) and applied it to face recognition. Lahdenoja et al. [15] proposed the symmetry ULBP which reduces the number of codes in the ULBP using the symmetry level of the code. However, it has not been proven that these patterns are effective in both minimizing the number of codes and reducing the classification results. The proposed method overcomes the disadvantages of LBP and other local binary approaches for efficient face recognition. The proposed method recognizes the image is facial or not based on the features extracted from image. The statistical features are extracted from FIDRSP model.

Greylevel co-occurrence matrices (GLCM) introduced by Haralick attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels[23]. One of the major inconveniences of GLCM is the large range of its possible values (256 grey values) at the same time that these values are not correlated. It also requires more computation time. In general, the size of co-occurrence matrix depends on grey level range of the image. To reduce grey values on images and also to reduce overall dimension of the image, the present paper derived a new model called FIDRSP on facial images. The proposed FIDRSP model 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 rest of the paper is organized as follows .The section 2 describes the methodology, section 3 presents experimental results. The comparison with other works and conclusions are specified in section 4 and 5 respectively.

2. METHODOLOGY FOR GENERATING FIDRSP FACE RECOGNITION MODEL

The block diagram of FIDRSP face recognition model is shown in Fig.1.

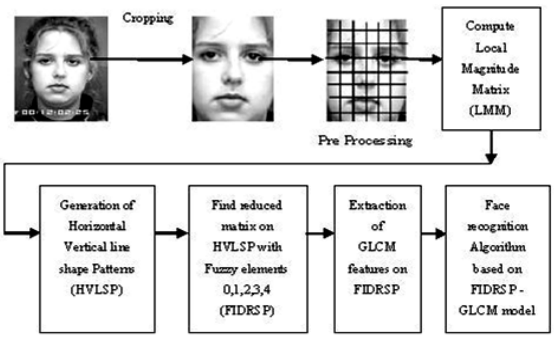

Fig.1. Block diagram of FIDRSP face recognition model

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.2 shows an example of the original face image and the cropped image.

Step 2: The proposed IDRSP method 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 Eq.(1) along the horizontal and vertical scan lines.

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

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.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 window 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: $V = \{V_1, V_2,...V_8, cp\}$, here cp represents the grey value of the centre pixel and V_1, V_2,...V_8 represents grey level intensity of neighboring pixels as shown in Fig.3(a). The LMM neighborhood pixel are obtained by evaluating the absolute difference between the neighboring pixel and the cp, as described in Eq.(2) and as shown in Fig.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.3. (a) a 3 × 3 neighborhood; (b) Local magnitude matrix(LMM)

$$LM_i = \text{abs}(V_i - cp)\ i = 1, 2,\ldots\ldots 8 \qquad (2)$$

Here LM_i represents the local magnitude of the neighboring pixels. Eq.(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 × 3 LMM, without central pixel. The HVLSP's on LMM is not considered central pixel because its grey level value is always zero. The average of these HVLSP's generates IDRSP with 2 × 2 dimension as shown in Fig.4 and as represented in Eq.(3) to Eq.(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. Construction of IDRSP model (a) LMM of a 3 × 3 neighbourhood; (b) IDRSP matrix obtained from HVLSP's of LMM

$$HVLSP_1 = \frac{(LM_1 + LM_2 + LM_3)}{3} \tag{3}$$

$$HVLSP_2 = \frac{(LM_1 + LM_4 + LM_6)}{3} \tag{4}$$

$$HVLSP_3 = \frac{(LM_6 + LM_7 + LM_8)}{3} \tag{5}$$

$$HVLSP_4 = \frac{(LM_3 + LM_5 + LM_8)}{3} \tag{6}$$

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, Texture Unit (TU) and other local approaches. The disadvantages of these approaches are for example if the difference between central pixel and neighboring pixel ranges from 1 to 255,then the above methods replace neighboring pixel values as 1 and if there is no difference these methods replace neighboring pixel as 0. That is most of the local approaches treats even the difference ranges from minimum to maximum as homogeneous. This clearly indicates that patterns will never gives useful information, which 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 paper considers five possible fuzzy grey values, but at any time only a maximum of four fuzzy grey levels will appear because of four pixels in the IDRSP model of 2 × 2.

The fuzzy membership function is shown in Fig.5. The following Eq.(7) is used to determine the fuzzy elements on IDRSP model of 2 × 2 neighborhood.

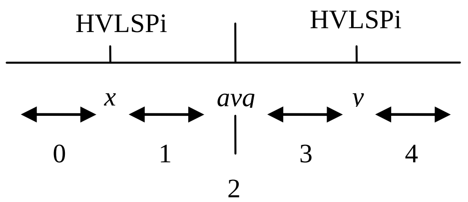

Fig.5. Fuzzy membership function representation

$$FE_i = \begin{cases} 0 & \text{if } HVLSP_i < avg \text{ and } HVLSP_i < x \\ 1 & \text{if } HVLSP_i < avg \text{ and } HVLSP_i > x \\ 2 & \text{if } HVLSP_i = avg \text{ and } \\ 3 & \text{if } HVLSP_i > avg \text{ and } HVLSP_i > y \\ 4 & \text{if } HVLSP_i > avg \text{ and } HVLSP_i < y \end{cases} \quad \text{for } i = 1,2,3,4 \tag{7}$$

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.6. The process of evaluating Fuzzy IDRSP model (a) sample IDRSP model; (b) FIDRSP model

The proposed FIDRSP method using HVLSP reduces the 3 × 3 neighbourhood in to a 2 × 2 and also it reduces the grey level range from 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. [24], 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: Grey Level Co-occurrence Matrices (GLCM) introduced by Haralick attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels [23]. One of the major inconveniences of GLCM on the original images is the huge range of its possible grey level values (0 to 255 or 1024 etc.) at the same time that these values are not correlated. It also requires more computation time. In general, the size of GLCM depends on grey level range of the image. To reduce grey range on images and also to reduce overall dimension of the image while preserving the significant features, the present research derived 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 on GLCM for effective face recognition. These features are Contrast, energy, local homogeneity and correlation represented from Eq.(8) to Eq.(11). The proposed FIDRSP model using GLCM combines the merits of both statistical and structural information of images and thus represents complete information of the facial image.

$$Contrast = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij} \tag{8}$$

$$Energy = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right)^2 \tag{9}$$

$$Local\ Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+\left(i-j\right)^2} \tag{10}$$

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij}\, \frac{\left(i-\mu\right)\left(j-\mu\right)}{\sigma^2} \tag{11}$$

where, P_{ij} is pixel intensity at position (i, j), μ and σ are mean and standard deviation.

3. RESULTS AND DISCUSSIONS

The proposed FIDRSP with GLCM features is applied for accurate recognition of human faces. The proposed FIDRSP model established a database of the 1002 face 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 of images are shown in Fig.7.

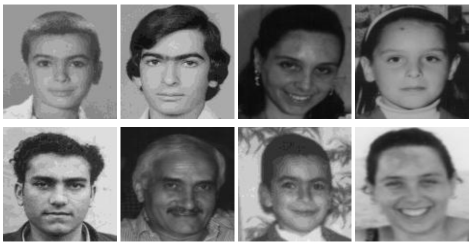

Fig.7. FGNET aging database from top to bottom and left to right; 01A08, 001A16, 002A31, 002A05, 004A21, 004A53, 001A05, 002A26

Fig.8. Scanned Images: sca.img-1,sca.img-2,sca.img-3,sca.img-4

The features of GLCM contrast, correlation, energy and 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.1 represents the derived four features on GLCM on 20 facial images. The facial recognition algorithm on the proposed FIDRSP is represented in algorithm one.

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

Begin

Input: The test facial Image.

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

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

Step 3: Find the difference between test 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

Table.1. GLCM feature set values on FIDRSP facial images

Sl. No.	Image name	Contrast	Correlation	Energy	Homogenity
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	004A19	6.33484	0.0817687	0.7466365	0.886877832
13	004A21	6.38258	0.1056107	0.7410726	0.886025302
14	003A58	6.60982	0.1074603	0.7321671	0.881967523
15	004A26	7.13350	0.1052307	0.7129096	0.872616125
16	004A53	6.86221	0.1059765	0.7229217	0.877460586
17	sca.img-1	4.77642	0.1236211	0.8007962	0.914706858
18	sca.img-2	6.53225	0.1353741	0.730277	0.883352692
19	sca.img-3	5.96058	0.0952838	0.7586969	0.893561025
20	sca.img-4	5.47673	0.0976771	0.7768536	0.902201327

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 Table.2 and Table.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 'one' and 'miss' indicates an unsuccessful recognition with value 'zero'. The hit or miss count for each time of the facial images 001A29, 001A40, 001A19, 003A20, 003A35 and 004A21 from FG-NET aging database and some images sc.img-1, sca.img-2 and sca.img-3 from scanned photographs are given in Table.4 and Table.5 respectively. Fig.9 and Fig.10 indicate the Bar graph for successful recognition rates of individual facial images of FG-NET aging databases and some images from scanned photographs.

Table.2. FIDRSP-GLCM features of facial image: 001A05 for ten times

Test No.	Contrast	Correlation	Energy	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.3. FIDRSP-GLCM features of facial image: sca.img-3 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. Recognition sequence of the facial images from the FG-NET aging database

Sl. No.	Hit Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
(a) 001A29	

Sl. No.	Hit Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	0
9	1
10	1
(b) 001A40	

Sl. No.	Hit Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
(c) 001A19	

Table.5. Recognition sequence of the facial images from the scanned photographs

Sl. No.	Hit Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
(a) sca.img-1	

Sl. No.	Hit Miss
1	1
2	1
3	1
4	1
5	0
6	1
7	1
8	1
9	1
10	1
(b) sca.img-2	

Sl. No.	Hit Miss
1	1
2	0
3	1
4	0
5	1
6	1
7	1
8	1
9	1
10	1
(c) sca.img-3	

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%.

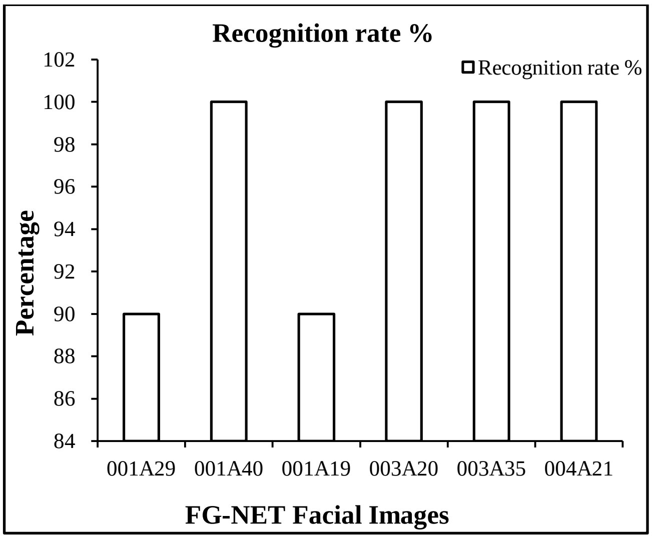

Fig.9. Bar graph for successful recognition rates of FG-NET aging database using FIDRSP model

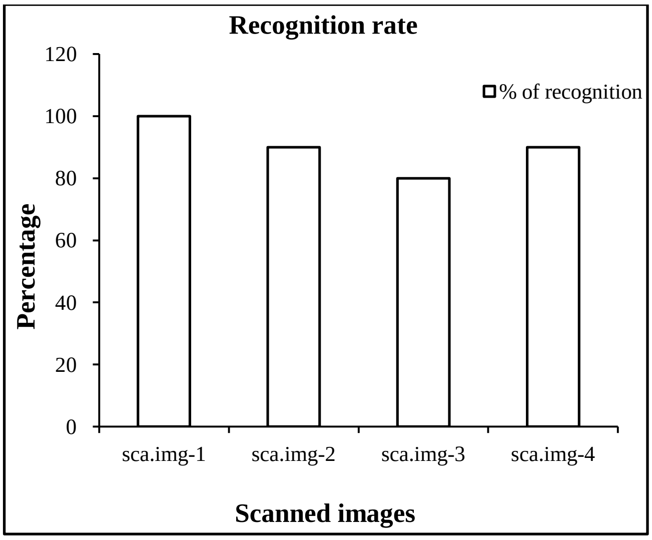

Fig.10. Bar graph for successful recognition rates of Scanned aging database using FIDRSP model

4. EVALUATION OF THE PROPOSED FIDRSP WITH OTHER METHODS

The proposed FIDRSP model with GLCM features is compared with other existing methods like Statistical Texture Features (STF) of Vijaya kumar and Chandra Mohan et al. [25] and Payman Moallema et al. [26]. From Table.6, 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.11.

Table.6. The face recognition rate by the proposed and other existing methods

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

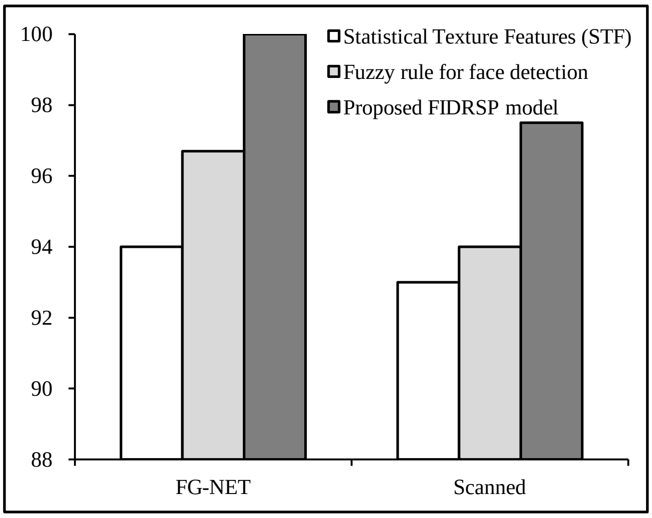

Fig.11. Face recognition chart of proposed FIDRSP model with GLCM features with other existing methods

5. CONCLUSION

The proposed FIDRSP model reduces the overall dimensionality of the image into (2N/3*2M/3) by using HVLSP, 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 IDRSP 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.

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REFERENCES

[1] Turk M and Pentland A, "Eigenfaces for recognition", *Journal of Cognitive Neuroscience* ,Vol. 3, No. 1, pp.72–86, 1991.

[2] Belhumeur P, Hespanha J and Kriegman D, "Eigenfaces vs. fisherfaces: class specific linear projection", *IEEE Transactions on Pattern Analysis and Machine Intelligence* , Vol. 19 , No. 4, pp. 711–720, 1997.

[3] Bartlett M, Movellan J and Sejnowski T, "Face recognition by independent component analysis", *IEEE Transactions on Neural Networks*, Vol. 13, No. 6, pp. 1450–1464, 2002.

[4] Heisele B, Ho Y and Poggio T, "Face recognition with support vector machines: global versus component-based approach", *Proceedings of the International Conference on Computer Vision*, pp. 688–694, 2001.

[5] Penev and Atick, "Local feature analysis: A general statistical the object representation", *Network: Computation in Neural Systems*, Vol. 7, No. 3, pp.477–500, 1996.

[6] Gabor D, "Theory of communication. Part 1: The analysis of Information", *Journal of the* Institution of Electrical *Engineers – Part III: Radio and Communication Engineering*, Vol. 93, No. 26, pp. 429–441, 1946.

[7] Wiskott, Fellous, Krüger, and C. von der Malsburg, "Face recognition by elastic bunch graph matching", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 19, No. 7, pp. 775–779,1997.

[8] Heisele B, Serre T and Poggio, "A component-based framework for face detection and identification", *International Journal of Computer Vision*, Vol. 74, No. 2, pp. 167–181, 2007.

[9] Ahonen T, Hadid A and Pietikainen M, "Face recognition with local binary patterns", *Proceedings of the Eighth European Conference on Computer Vision*, pp. 469–481, 2004.

[10] Zhang L, Chu R, Xiang S, Liao S and S.Z. Li, "Face detection based on multi-block LBP representation", *Proceedings of the Second International Conference on Biometrics*, pp. 11–18, 2007.

[11] Ojala T, Pietikainen M and Harwood D, "A comparative study of texture measures with classification based on feature distributions", *Pattern Recognition* ,Vol. 29, No. 1, pp. 51–59,1996.

[12] Ojala T, Pietikainen and Maenpaa P, "Multiresolution greyscale and rotation invariant texture classification with local binary patterns", *IEEE Transactions of Pattern Analysis and Machine Intelligence*, Vol. 24, No. 7, pp. 971–977, 2002.

[13] Jin H, Liu Q, Lu H and Tong X, "Face detection using improved LBP under Bayesian framework", *Proceedings*

of the Third International Conference on Image and Graphics, pp. 306–309, 2004.

[14] Ahonen T, Hadid A and Pietikainen M, "Face description with local binary patterns: application to face recognition", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 28, No. 12, pp. 2037–2041, 2006.

[15] Lahdenoja O, Laiho M and Paasio A, "Reducing the feature vector length in local binary pattern based face recognition", *Proceedings of the IEEE International Conference on Image Processing*, pp. 11–14, 2005.

[16] Liao S, Zhu X, Lei Z, Zhang L and Li S Z, "Learning multi-scale block local binary patterns for face recognition", *Proceedings of the Second International Conference on Biometrics*, pp. 828–837, 2007.

[17] Heusch G, Rodriguez Y and Marcel S, "Local binary patterns as an image preprocessing for face authentication", *Proceedings of the Seventh International Conference on Automatic Face and Gesture Recognition*, pp. 9–14, 2006.

[18] Rodriguez Y, "Face authentication using adapted local binary pattern histograms", *Proceedings of the 10^{th} European Conference on Computer Vision*, pp. 321–332, 2006.

[19] Shan, Gong and McOwan, "Facial expression recognition based on local binary patterns: a comprehensive study", *Image and Vision Computing*, Vol. 27, No. 6, pp. 803–816, 2009.

[20] Kellokumpu V, Zhao G, Li S. Z and Pietikainen M, "Dynamic texture based gait recognition", *Advances in Biometrics, Lecture Notes in Computer Science*, Vol. 5558, pp. 1000-1009, 2009.

[21] Takala V, Ahonen T and Pietikainen M, "Block-based methods for image retrieval using local binary patterns", *Proceedings of the 14^{th} Scandinavian Conference on Image Analysis*, pp. 882–891, 2005.

[22] Heikkil M, Pietikainen M and Heikkil J, "A texture-based method for detecting moving objects", *Proceedings of the 15^{th} British Machine Vision Conference*, pp.187–196, 2004.

[23] Haralick R. M, Shanmugan K and Dinstein I, "Textural features for image classification", IEEE Transactions *on* Systems, Man *and* Cybernetics, Vol. SMC-3, No. 3, pp. 610-621, 1973.

[24] Narayanan R.M, T. S. Sankaravadivelu and Reichenbach S. E, "Dependence of image information content on grey-scale resolution", P*roceedings of International Geoscience and Remote Sensing Symposium*, Vol. 1, pp. 153-155, 2000.

[25] Chandra Mohan M, V. Vijaya Kumar and U S N Raju, "New Face Recognition Method Based on Texture Features using Linear Wavelet Transforms", *International Journal of Computer Science and Network Security*, Vol. 9, No. 12, pp. 223-230, 2009.

[26] Payman Moallema, Bibi Somayeh Mousavi and S. Amirhassan Monadjemi, "A novel fuzzy rule base system for pose independent faces detection", *Applied Soft Computing*, Vol. 11, No. 2, pp. 1801–1810, 2011.