Local Directional Pattern based Fuzzy Co-occurrence Matrix Features for Face recognition

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Abstract--- This paper proposes a method for extracting GLCM Features on Local Directional Pattern based Fuzzy Co-occurrence matrix for effective face recognition. In this method Local Directional Pattern is computed on the image and then fuzzy representation is used for reduction of image edge responsiveness values. Contrast, correlation, energy and homogeneity features are evaluated over Co-occurrence matrices of LDP based fuzzy matrix in four directions 0°, 45°, 90° and 135°. Face recognition algorithm is proposed with these features. The proposed method has been intensively evaluated by applying recognition tests on FGNET and scanned facial images. The results show that this proposed method is superior to the performance obtained using the existing face recognition methods.

Keywords: Face recognition, LDP based Fuzzy Co-occurrence Matrix, GLCM Features, LDPFM.

I. INTRODUCTION

Face Recognition is a long-standing problem in computer vision and pattern recognition. It is used in various applications like crime detection surveillance, passport, security, human computer interaction, etc. Face recognition methods are broadly categorized into two types geometry based feature methods, which use global information as features, and appearance based feature methods, uses describe the texture of the face as features. Many methods are developed for facial images analysis [1], which include such techniques as principal component analysis (PCA) [2], linear discriminate analysis (LDA) [3], independent component analysis (ICA) [4], and support vector machine (SVM) [5]. Next structural approach for face analysis using Local Binary Pattern (LBP) developed [6], which showed a high discriminative power for texture classification due to its invariance to monotonic gray level changes. After that, many variants of LBPs have been introduced by many other researchers and applied to many areas such as face detection [7-9], face recognition [10-13], face authentication [14-15], facial expression recognition [16], gate recognition [17], image retrieval [18], age classification [19-22] and object detection [23]. To address this face recognition issue, in this paper we proposed a method, it evaluates LDP based Fuzzy matrix on facial images and then GLCM Features are extracted for face recognition. The remainder of this paper is organized as follows. Section II describes methodology. In Section III, the experimental results with comparison are reported. Finally Section IV concludes this paper.

II. METHODOLOGY

In this proposed method the color image is converted to gray image, on this image the Local Directional Pattern (LDP) is computed and then Fuzzy Logic is applied and Co-occurrence matrix features are evaluated for face recognition. This method is explained in the following sub sections in detail.

Step1: Color image to gray image conversion

The given color image is converted into a grey level image using RGB color quantization method.

Step2: Local Directional Pattern

The present research uses a Local Directional Pattern concept [11], which overcomes the drawbacks of LBP and is more robust for classification. The local descriptor LDP considers the edge response values in all different directions instead of surrounding neighboring pixel intensities. The LDP is an eight bit binary code assigned to each pixel of an input image. This pattern is calculated by comparing the relative edge response value of a pixel in different directions. For this purpose, the present paper evaluates LDP as eight directional edge response value of a particular pixel using Kirsch masks in eight different orientations (M0-M7) centered on its own position. These masks are shown in the Fig.1. By applying eight masks, eight edge response values m0, m1, …, m7 are obtained, each representing the edge significance in its respective direction. The response values are not equally important in all directions. The LDP is formed considering only first three values of sorted edge responses in descending order.

-3	-3	5
-3	0	5
-3	-3	5

M0

-3	5	5
-3	0	5
-3	-3	-3

M1

5	5	5
-3	0	-3
-3	-3	-3

M2

5	5	-3
5	0	-3
-3	-3	-3

M3

5	-3	-3
5	0	-3
5	-3	-3

M4

-3	-3	-3
5	0	-3
5	5	-3

M5

-3	-3	-3
-3	0	-3
5	5	5

M6

-3	-3	-3
-3	0	5
-3	5	5

M7

Fig.1: Kirsch edge response masks in eight directions.

Step 2: Formation LDP based Fuzzy Matrix

The proposed method labels eight neighbors of a 3×3 neighborhood of LDP of image using five possible fuzzy patterns or values {0, 1, 2, 3 and 4} derived from the fuzzy code or representation as depicted in equation 3.The element V_i represent the LDP values of the eight neighboring LDP values on a 3×3 neighborhood of LDP textured image, V_0 represents the LDP of central pixel, x and y are the user specified lag values. The process of evaluating fuzzy values on a 3×3 neighborhood of LDP image is shown in figure 2. By repeating this process over the entire LDP image, LDP based Fuzzy Matrix is computed. This reduces the LDP values with range 0 to 4 values. This reduction is based on the assumption that the face image classification is a data generalization process and reducing local information 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.

$$E_i = \begin{Bmatrix} 0 & \text{if} & V_i < V_0 & \text{and} & V_i < x \\ 1 & \text{if} & V_i < V_0 & \text{and} & V_i > x \\ 2 & \text{if} & V_i = V_0 & & \\ 3 & \text{if} & V_i > V_0 & \text{and} & V_i > y \\ 4 & \text{if} & V_i > V_0 & \text{and} & V_i < y \end{Bmatrix} \quad \text{for } i = 1,2,3,\dots,8 \qquad (1)$$

74	130	120
100	140	20
150	170	25

0	1	1
1	2	0
3	4	0

Fig.2: (a) LDP of image (b) Fuzzy values

Step 3: Evaluation of GLCM Features on LDP based Fuzzy Co-occurrence Matrix (LDPFCM)

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 [25]. 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. The present method evaluates the feature set contrast, correlation, energy, and, local homogeneity on reduced local information LDPFCM. These features are computed using the equations 2 to 5 on LDPFM in four directions 0°, 45°, 90° and 135° for effective face recognition.

$$contrast = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \quad (2) \qquad Energy = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \quad (3)$$

$$Local\ Homogenity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (4) \qquad Correlation = \sum_{i,j=0}^{N-1} P_{ij}\frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (5)$$

III. RESULTS AND DISCUSSIONS

The proposed method LDPFCM with GLCM features is applied for accurate recognition of human faces. This method established a database of the 1002 face images collected from FG-NET database and other 600 images collected from the scanned photographs. Sample images of each group of images are shown in figure 3.

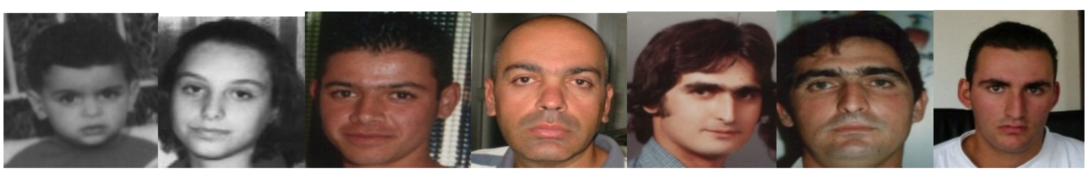

Fig. 3: Sample images from FG-NET Database

The features contrast, correlation, energy and homogeneity are extracted on LDP based Fuzzy Co-occurrence Matrix of considered database images and the results are stored in the feature vector. Feature set leads to representation of the training images. Tables 1,2,3 and 4 represent the derived four features in four directions with 0° 45°, 90° and 135° orientation of LDPFCM on 5 facial images. These 16 features are used as feature vector for each face in recognition. The facial recognition algorithm with this feature vector on LDPFCM is represented in algorithm1. This algorithm is tested on considered facial image data set and has shown 98% successful recognition rate.

Table 1: GLCM Feature set on LDPFCM 0° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	048A52	12.8964	0.1101	0.5103	0.7697
2	049A17	12.7105	0.0595	0.5321	0.7730
3	053A18	9.4356	0.1280	0.6237	0.8315
4	069A13	11.3173	0.1163	0.5610	0.7979
5	072A34	11.5335	0.0917	0.5609	0.7940

Table 2: GLCM Feature set on LDPFCM 45° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	048A52	14.3908	0.0068	0.4969	0.7430
2	049A17	13.1020	0.0267	0.5294	0.7660
3	053A18	10.4956	0.0299	0.6109	0.8126
4	069A13	12.4733	0.0215	0.5501	0.7773
5	072A34	12.4344	0.0159	0.5528	0.7780

Table 3: GLCM Feature set on LDPFCM 90° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	048A52	13.6060	0.0610	0.5037	0.7570
2	049A17	12.9004	0.0416	0.5314	0.7696
3	053A18	9.7406	0.1061	0.6183	0.8261
4	069A13	11.6679	0.0901	0.5569	0.7916
5	072A34	11.6346	0.0843	0.5596	0.7922

Table 4: GLCM Feature set on LDPFCM 135° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	048A52	14.4373	0.0037	0.4965	0.7422
2	049A17	13.5718	-0.0082	0.5250	0.7576
3	053A18	10.4292	0.0360	0.6117	0.8138
4	069A13	12.4930	0.0200	0.5499	0.7769
5	072A34	12.3119	0.0256	0.5540	0.7801

Algorithm 1: Face recognition algorithm on LDP based Fuzzy Co-occurrence Matrix using GLCM Features.

Begin

Input: The test facial Image.

Step1: Convert the given test image into LDP based Fuzzy Co-occurrence Matrix.

Step2: Evaluate the contrast, correlation, energy and homogeneity features on LDPFCM of test images.

Step3: Find the difference between test image features with existing feature vector of the feature library.

Step4: 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

The proposed method GLCM Features on LDP based fuzzy matrix is compared with other existing methods like Statistical Texture Features by Vijaya kumar et.al. [26] and fuzzy rule for face detection by Moallema et.al. [27] and FIDRSP model by P. Chandra Sekhar Reddy et.al. [28]. The percentage mean recognition rate for the proposed and other existing methods is shown in Table 5.

Table 5. The face recognition rate by the proposed and other existing methods.

Image Database	**Statistical Texture Features [26]**	**Fuzzy rule for face detection [27]**	**FIDRSP model [28]**	**Proposed LDPCM Features method**
FG-NET	94	96.7	100	100
Scanned	93	94	97.5	98

IV. CONCLUSION

The proposed method with GLCM features on LDPFCM gathers local edge directional information of facial image and then fuzzy matrix is computed. This LDPFM contains values only from set {0, 1, 2, 3, 4}, reducing the overall complexity in co-occurrence matrix formation. The proposed method only by evaluating four GLCM features of LDPFCM has shown a good recognition rate. By comparing the performance of the proposed method with the existing methods, it shows that our method is best suited for face recognition system.

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