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Central Local Directional Pattern Value Flooding Co-occurrence Matrix based Features for Face Recognition

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Abstract--- In this paper proposed a method for extracting Contrast, Correlation, Energy, and, Local homogeneity features on Central Local Directional Pattern Value Flooding Matrix for face recognition. Local Directional Pattern is computed on the image and then Central Local Directional Pattern Value Flooding Matrix is formed, and on this matrix Contrast, correlation, energy and homogeneity features are evaluated in four directions 0°, 45°, 90° and 135°. Face recognition algorithm is proposed with this feature set. The proposed method has been tested on FGNET and scanned facial images. The results shown that proposed method is superior in recognizing faces compared to the other existing face recognition methods.

Keywords: Face recognition, LDP, Central Local Directional Pattern Value Flood Co-occurrence Matrix

I. INTRODUCTION

Face recognition methods have attracted much attention in the field of pattern classification and computer vision over the past two decades. 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 problem, in this paper we proposed a method, it evaluates LDP based flood matrix on facial images and then 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 conclusion is drawn in Section IV.

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 Central Local Directional Pattern Value Flood is formed in 3x3 blocks on entire image. Statistical 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 method using a Local Directional Pattern [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. This LDP is computed on entire image with 3x3 block sizes.

-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-3: Computing Central Local Directional Pattern Value Flooding Matrix (CLDPVFM)

The central local directional pattern value flooding forms a group of LDP values which have the LDP value as the central LDP over the 3x3 neighborhood. In the 3x3 neighborhood, for all the neighbors which have the same LDP value as the center pixel, then these values are kept unchanged otherwise, it is set to zero. The 3x3 block obtained from this process is called a central ldp value flooding. The CLDPVFM is computed over the whole image is described as follows.

(1) Central ldp value floodings I1(x,y), I2(x,y), I3(x,y) and I4(x,y) are computed starting from position (1,1), (1,2), (2,1) and (2,2) respectively with 3x3 block from left-to-right and top-to-bottom throughout LBP image I(m,n) with a step-length of three along both horizontal and vertical directions.

(2) The final Central Local Binary Pattern Value Flooding Matrix, denoted by CLDPVFM (x,y) is computed using equation 1.

CLDPVFM (x,y) = p (1)

Where p is avg (or) avg_g

avg= (I1(x,y) +I2(x,y)+ I3(x,y)+ I4(x,y)) /r , r is the number of non-zero intensity values .

avg_g = a value which is just greater than avg and equal to one of four intensity values I1(x,y), I2(x,y), I3(x,y) and I4(x,y) at position (x,y).

An example of central ldp value flood detection is shown in Fig.2.

6	7	6
6	6	4
5	6	9

(a) 3x3 block with gray values

6	0	6
6	6	0
0	6	0

(b) Central ldp value flood

Fig.2. Detection of Central Local Directional Pattern Value Flood

Step 3: Evaluation of Statistical Features on Central Local Directional Pattern Value Flood Co-occurrence Matrix

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]. The present method evaluates the feature set contrast, correlation, energy, and, local homogeneity on Central Local Directional Pattern Value Flood Co-occurrence matrix. These features are computed using the equations 2 to 5 on CLDPVFM in four directions 0°, 45°, 90° and 135° for face recognition.

$$\text{contrast} = \sum_{i,j=0}^{N-1} -\ln\left(P_{ij}\right) P_{ij} \qquad (2)$$

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

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

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

3. RESULTS AND DISCUSSIONS

The proposed method established a database of the 1002 face images collected from FG-NET database and other 600 images collected from the scanned photographs and sample of these images are shown in Fig.3.

Fig. 3: Sample images from FG-NET Database

The Haralick features contrast, correlation, energy and homogeneity are extracted on Central Local Directional Pattern Value Flood Co-occurrence matrix of considered face image database and are stored as a feature vector. Feature set leads to representation of the training set for images. Tables 1, 2, 3 and 4 represent the derived four features in four directions with 0° 45°, 90° and 135° orientation of CLDPVFM on 5 facial images. These 16 features are used as feature vector for each face in recognition. The facial recognition algorithm is defined and tested on considered face image database and has shown 98.5 % successful recognition rate.

Table 1: Contrast, Correlation, Energy, and, Local homogeneity features on CLDPVFM 0° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	011A05	16.05651	0.169036	0.385351	0.713277
2	007A22	16.43094	0.140555	0.386959	0.70659
3	030A26	17.51641	0.113561	0.367042	0.687207
4	007A45	15.57964	0.056519	0.446153	0.721792
5	029A29	16.7141	0.114613	0.389988	0.701534

Table 2: Contrast, Correlation, Energy, and, Local homogeneity features on CLDPVFM 45° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	011A05	19.78993	-0.02617	0.365667	0.646608
2	007A22	20.02701	-0.04931	0.368826	0.642375
3	030A26	19.89439	-0.00806	0.356075	0.644743
4	007A45	17.26247	-0.04885	0.43593	0.691742
5	029A29	18.95312	-0.00322	0.377257	0.661552

Table 3: Contrast, Correlation, Energy, and, Local homogeneity features on CLDPVFM 90° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	011A05	16.14655	0.162255	0.385722	0.711669
2	007A22	17.04846	0.108652	0.382791	0.695563
3	030A26	17.26153	0.126831	0.368379	0.691758
4	007A45	15.05272	0.088677	0.450089	0.731201
5	029A29	16.5987	0.120315	0.390922	0.703595

Table 4: Contrast, Correlation, Energy, and, Local homogeneity features on CLDPVFM 135° of facial images.

S.no	Image name	Contrast	Correlation	Energy	Homogeneity
1	011A05	19.84542	-0.02905	0.365449	0.645617
2	007A22	19.87251	-0.0412	0.369419	0.645134
3	030A26	19.88025	-0.00734	0.356136	0.644996
4	007A45	17.28273	-0.05006	0.435828	0.69138
5	029A29	18.98252	-0.00477	0.377122	0.661026

Algorithm 1: Face recognition algorithm on CLDPVFM using feature set.

Begin

Input: The test facial Image.

Step1: Convert the given test image into CLDPVFM.

Step2: Evaluate the contrast, correlation, energy and homogeneity features on CLDPVFM 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 with Features CLDPVFM is compared with other existing methods like Statistical Texture Features by Vijaya kumar et.al. [24] and fuzzy rule for face detection by Moallema et.al. [25]. The percentage mean recognition rate for the proposed and other existing methods is shown in Table 5. The proposed method has shown 98.5 % successful recognition rate for FG-Net and scanned images.

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

Image Database	Statistical Texture Features [24]	Fuzzy rule for face detection [25]	Proposed method features on CLDPVFM
FG-NET	94	96.7	98.5
Scanned	93	94	98.3

IV. CONCLUSION

The proposed method CLDPVFM with features gathers local edge directional information of facial image and then the flood of central ldp value is formed on entire image is used to find the features. These features Contrast, Correlation, Energy, and, Local homogeneity are recognizing faces very effectively. This method is very simple and efficient. The proposed method has shown a high recognition rate over the other existing methods.

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