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A New Approach for Face Recognition and Age Classification using LDP

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Abstract— The present paper proposes a novel local texture features on facial images that recognise facial images based on the Morphological primitive patterns with grain components (MPP-g) on a Local Directional Pattern (LDP). A LDP feature is obtained by computing the edge response values in all eight directions at each pixel position and generating a code from the relative strength magnitude. The local descriptor LDP is more consistent in the presence of noise, and illumination changes, since edge response magnitude is more stable than pixel intensity. The present paper proposes Morphological primitive patterns with grain components (MPP-g) which are rotationally and pose invariant for face recognition and age classification. The experimental result on FGnet database images shows the efficacy of the proposed method.

Index Terms— Image classification; shape representation; morphological operation; Hu moment invariants; boundary extraction; preprocessing techniques; structuring element.

1 Introduction

Humans have a remarkable ability to recognize faces and to use them to distinguish between people. Face recognition as a "biometric" technology has become a hot topic in modern day research. Face recognition has received substantial attention from researchers in biometrics, pattern recognition, and computer vision communities [1, 2, 3, and 4]. Face recognition methods have a wide range of commercial, surveillance and law enforcement applications such as smart cards, access control, passports, credit cards, driving licenses, biometric authentication, video surveillance, and information security, among others. Face recognition or face identification compares an input image (probe) with a database (gallery) and reports a match, if any. The purpose of face authentication is to verify the claim of the identity of an individual in an input image.

A survey of early face recognition methods before 1991 was written by Samal and Iyengar, [5]. Chellapa et al. wrote a more recent survey on face recognition and some detection methods [1]. The feature-based and the neural-network-based techniques, of FRMs are surveyed by Smal et l. and Valentin et al. [5, 6], the automatic facial expression analysis, is surveyed by Pantic and Rothkrantz [7], where as several critical issues involved in an effective face recognition system are pointed out by Daugman [8]. Many of the latest techniques are reviewed by the recent comprehensive survey [9]. A thorough qualitative analysis of the many different face recognition algorithms were done by Zhao et al. [9]. A good face recognition performance across illumination and pose variations was achieved recently [10, 11]. Many methods were proposed in the literature for identifying facial expressions from face images [12, 13]. Facial Action Coding systems have contributed significantly towards characterizing facial expressions.

A multilinear discriminant analysis (MDA) algorithm is proposed [14] for face recognition, which is meant for classification problems involving higher order tensors. The MDA algorithm based on higher order tensors has the potential to outperform the traditional vector-based subspace learning algorithms, especially in the cases with small sample sizes. But this algorithm is computationally very expensive. And they are rotationally variant. The disadvantage of using Geometric Deformation Features and Support Vector Machines [15] for facial expression recognition method is, the user has to manually place some of Candide grid nodes to face landmarks of the image sequence under examination. A robust face recognition method based on histogram of Gabor phase pattern (HGPP), is proposed recently [16]. In HGPP, Global Gabor phase pattern and local Gabor phase pattern are proposed to encode the phase variations. The nearest-neighbor classifier with histogram intersection as the similarity measurement is used for face recognition. The influence of the embedding space geometry and dimensionality choice on the representation accuracy of face recognition is addressed recently [17]. For a reliable face recognition a one-dimensional correlation filter based class-dependence feature analysis (1D-CFA) method [18] is proposed. This is designed in the low dimensional principal component

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analysis (PCA) subspace, for effective feature extraction.

The present paper assumes that the facial skin texture attributes can be evaluated with tonal primitives or local properties. An image texture is described by the number and types of its primitive patterns or shapes. To evaluate topological or structural changes on a facial skin the present paper used morphological properties. Each of these properties translates some property of the primitives and the spatial interaction between the primitives. By utilizing these concepts of textures the present paper proposes a new technique of face recognition based on MPP-g on LDP.
The present paper is organized as follows. The proposed methodology is described in section 2, section 3 deals with results and discussions and conclusions are given in section 4.

2 Methodology

2.1 Local Directional Pattern

The proposed paper uses a LDP concept [19], which overcomes the drawbacks of LBP. The local descriptor LDP considers the edge response values in all different directions instead of surrounding neighbouring pixel intensities like LBP. This provides more consistency in the presence of noise, and illumination changes, since edge response magnitude is more stable than pixel intensity. The LDP is based on LBP. The LBP operator, a gray-scale invariant texture primitive, has gained significant popularity for describing texture of an image [20]. It labels each pixel of an image by thresholding its P-neighbor values with the centre value by converting the result into a binary number by using Equation 1.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \tag{1}$$

Ojala et al. [20] also observed that in significant image area certain local binary patterns appear frequently. These patterns are named as “uniform LBP” as they contain very few transitions from 0 to 1 or 1 to 0 in circular bit sequence. Ahonen et al. [21] used this variant of LBP patterns which have atmost two transitions (LBPu2) for their face recognition. This variant of LBP is still sensitive to random noise and non-monotonic to illumination variation. To overcome this, the present paper used LDP technique with Kirsch edge response and with a morphological treatment for efficient face recognition. The proposed novel scheme contains four major steps.
Step 1: If the facial texture image is a color image then it is converted into a gray level facial image.
Step 2: The gray level facial image is converted into a binary image using LDP concept as explained in section B.
Step 3: The proposed Morphological Primitive Patterns from one grain to eight grains (MPP-1g to MPP-8g) are evaluated on LDP for each of the facial images.
Step 4: Based on step three the significant MPP-g is evaluated for the effective and accurate face recognition.

2.2 Local Directional Pattern (LDP) with Kirsch Edge Response

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 on LDP 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.

$$\underset{(M0)}{\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix}} \underset{(M1)}{\begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix}} \underset{(M2)}{\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}} \underset{(M3)}{\begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}}$$

$$\underset{(M4)}{\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix}} \underset{(M5)}{\begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}} \underset{(M6)}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix}} \underset{(M7)}{\begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}}$$

Fig. 1 Kirsch edge response masks in eight directions

Applying eight masks, eight edge response value 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 presence of corner or edge show high response values in particular directions.

The LDP code produces more stable pattern in presence of noise, illumination changes and various conversion schemes of color facial images into gray images. For instance, Fig.2 shows an original image and the corresponding image with illumination changes. After illumination change, 5th bit of LBP changed from 1 to 0, thus LBP pattern changed from uniform to a non-uniform code. Since gradients are more stable than gray value, LDP pattern provides the same pattern value even in the presence of noise and non-monotonic illumination changes.

85	32	26
53	50	10
60	38	45

LBP=0011**1**000
LDP=00010011

85	32	26
48	50	10
60	38	45

LBP=0010**0**000
LDP=00010011

Fig.2 Stability of LDP vs. LBP (a) Original Image (b) Image with Noise

2.3 Evaluation of Morphological Primitive Patterns with Grain Components (MPP-g) on LDP

On the binary LDP facial texture images of the previous step, the present paper evaluated the frequency of occurrence of MPP-g on a 3x3 mask. The age classification of the present paper is based on the number of grain components that occur in any order instead of calculating the frequency of occurrences of various patterns on a 3x3

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mask. This makes the present method as rotationally and poses invariant. Frequency occurrences of MPP-g in the present paper are counted if and only if the central pixel of the window is a grain. If the central pixel is not a grain then the window is treated as a zero grain component. In the following figures '0' indicates no grain and '1' indicates a grain. There can be 8 combinations of MPP-1g, which are shown in the Fig. 3. By any rotation the MPP-1g may change its position in 8 ways on a 3x3 mask as shown in Fig 3. The present method counts the frequency of occurrences of MPP-1g on a 3x3 mask irrespective of its position. Therefore the present method is rotationally invariant.

1	0	0
0	1	0
0	0	0

(a)

0	1	0
0	1	0
0	0	0

(b)

0	0	1
0	1	0
0	0	0

(c)

0	0	0
0	1	1
0	0	0

(d)

0	0	0
0	1	0
0	0	1

(e)

0	0	0
0	1	0
0	1	0

(f)

0	0	0
0	1	0
1	0	0

(g)

0	0	0
1	1	0
0	0	0

(h)

Fig. 3 Representation of MPP-1g

1	1	0
0	1	0
0	0	0

(a)

1	0	1
0	1	0
0	0	0

(b)

1	0	0
0	1	1
0	0	0

(c)

1	0	0
0	1	0
0	0	1

(d)

1	0	0
0	1	0
0	1	0

(e)

1	0	0
0	1	0
1	0	0

(f)

1	0	0
1	1	0
0	0	0

(g)

Fig. 4 Representation of MPP-2g by fixing one of the grain component at (0,0)

0	1	1
0	1	0
0	0	0

(a)

0	1	0
0	1	1
0	0	0

(b)

0	1	0
0	1	0
0	0	1

(c)

0	1	0
0	1	0
0	1	0

(d)

0	1	0
0	1	0
1	0	0

(e)

0	1	0
1	1	0
0	0	0

(f)

Fig. 5 Representation of MPP-2g by fixing one of the grain component at (0,1)

There will be 7 different formations of MPP's with two grain components (MPP-2g) by fixing one of the grains at pixel location (0,0) on a 3×3 mask as shown in Fig.4. In the similar way there will be 6 formations of MPP-2g by positioning one of the grains at the pixel location (0,1) as shown in Fig.5. Thus there will be 7! Ways of forming MPP-2g for a 3x3 window. In the same way there will be 6!, 5!, 4!, 3!, 2! and 1! ways of forming MPP-g of 3, 4, 5, 6, 7 and 8 respectively, on a 3x3 mask irrespective of their rotational position.

Fig. 6 Sample facial images of children with different poses of FGnet aging database

Fig. 7 Sample facial images of adults with different poses of FGnet aging database

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TABLE 1

FREQUENCY OF OCCURRENCES OF CHILD FACIAL IMAGES USING MPP-G

015A01	13451	1468	1288	1228	2209	4066	2155	895
002A03	17206	788	658	1009	833	1216	363	138
009A03	14478	1090	861	1052	1233	1763	1186	548
069A03	13081	1293	1276	1164	2372	4605	2996	1493
053A06	16566	620	640	917	1065	2490	2168	4414
066A06a	19661	1170	929	1138	1454	2221	1379	828
019A07	14369	1092	982	1163	1676	3527	2956	3015
016A08	14595	926	726	935	1153	2255	2626	5664
023A09	21243	1459	990	1183	1129	1521	774	581
073A09	10871	1186	1164	1122	2258	5396	3901	2482
065A09	11821	806	661	856	930	1774	1501	10531
011A11	17020	858	587	819	833	1253	611	230
022A11	22196	989	799	910	1092	1325	863	706
012A12	16829	923	690	1023	854	1080	617	195
008A13	14843	1421	1046	1162	1305	1389	746	299

TABLE 2

FREQUENCY OF OCCURRENCES OF ADULT FACIAL IMAGES USING MPP-G

Adult images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
027A41	15253	1594	1477	2057	2424	3758	1534	783
062A41	14390	2159	1912	2513	3067	4187	1770	578
071A42	20860	1351	1152	1471	1637	2585	998	522
033A44	19858	1290	1067	1621	1569	2188	852	435
047A45	14628	1643	1629	1936	2414	4082	2934	1310
028A46	19556	1065	910	1278	1395	2373	1587	716
045A48	23198	1298	1076	1254	1286	1654	586	224
003A49	22308	1374	981	1437	1105	1233	251	191
048A50	23498	996	854	1204	1165	1737	785	337
039A52	16538	2313	2169	2406	2635	3013	1143	359
004A53	18486	2046	1583	2037	2140	2855	1023	406
005A61	22360	1140	924	1273	1088	1400	514	281
006A61	20731	961	760	1282	1368	2220	1111	647

The facial image is recognized as child or adult based on Algorithm 1. From the computed frequency of occurrences of MPP-1g to MPP-8g by the Algorithm 1 the present paper observed that only 2 MPP-g are exhibiting successful Child-Adulthood Classification Rates (CACR). The MPP-1g and MPP-4g have proved to have significant, precise and accurate classification rates than others MPP-g's. The present paper suggests that it is not necessary to evaluate frequency occurrences of MPP-2g, MPP-3g, MPP-5g, MPP-6g, MPP-7g and MPP-8g on LDP, for the child and adult age classification. Since the facial images are of different poses, the proposed method is pose invariant. To prove the proposed method is rotationally invariant the MPP-g are evaluated with different rotations 30, 45 and 135 degrees and listed in Table 3 to Table 8. Even by rotation with different angles, the Algorithm 1 based on MPP-1g and MPP-4g classifies the child and adult. This proves that the present method is rotationally invariant. Thus the present method has overcome the disadvantage of pattern based and also previous methods which are rotational and pose variant.

Algorithm 1: Rotational and pose invariant child and adult age classification using MPP-g on LDP.

```
if (MPP-1g<=14000)
print (facial image is of Child)
elseif  (((MPP-1g >14000) && (MPP-1g <23500)) && ( MPP-4g<=1200))
          print (facial image is of Child)
elseif (((MPP-1g >14000) && (MPP-1g <23500)) && ((MPP-4g >1200) && …
      (MPP-4g < 2500)))
print (facial image is of Adult)
else
print (facial image is not of child and adult)
end
```

The Algorithm 1 classifies child from adult, based on only the frequency of occurrences of MPP-1g and MPP-4g values. If MPP-1g value is less than 14000 then the facial image is treated as child, else they form group 2 entries. By considering both MPP-1g and MPP-4g values if MPP-1g count is in between 14000 to 23500 and MPP-4g count is less than 1200 then it classifies as a child otherwise adult as specified in the Algorithm 1. The same thing is also true for all rotations performed on facial images.

3. Results and Discussions

The present paper counted the frequency of occurrences of MPP-g on LDP on 1002 images of FGnet as specified in the above section and placed them in the facial database. The Fig. 6 and Fig.7 shows some of the database images of Fgnet database with different aging sequence. The frequency occurrences of MPP-1g to MPP-8g on LDP facial images are evaluated and listed in Table 1 and Table 2. After a careful study on frequency occurrences of MPP-1g to MPP-8g the present study found that MPP-1g in all facial images occupies more than 55% of total occurrences. This indicates MPP-1g contains more textural and topological information of the facial skin on the rotated facial images of FGnet for recognition purpose. For evaluating successful recognition rate each facial image sample is tested ten times with different rotations. Each time, only the MPP-1g is evaluated. For this the present study also collected the following facial images of Fig 8, which are not part of the database images of the Fig.6 and Fig.7. In the present setup a test sample image is tested for 10 times with different rotations. The frequency of occurrences of MPP-1g on LDP with different rotations for ten times on the database facial images 009A03, 027A41 and non database facial images 028A26 and 028A23 are listed in Table 3. Each times the hit or miss count is measured based on the 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'. An unsuccessful

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recognition is also counted sometimes as successful, if the test sample facial image is not part of the original database.

The hit or miss count for each time of the data base facial images 009A03, 027A41 and non database facial images 028A26 and 028A23 are listed in the Table 4. For the facial images 028A26 and 028A23 the miss ratio indicates the successful recognition, because these facial images are not part of the database. The successful recognition rates of each facial image of the database and sample images are given in the form of bar graph in Fig. 9 respectively.


040A03b 037A06 030A18 028A26


027A20 024A23 022A27 022A1

Fig. 8 Some of the probe or sample facial images from FGnet aging database

TABLE 3
FREQUENCY OF OCCURRENCES OF MPP-1G ON LDP OF PROBE FACIAL IMAGES FOR TEN TIMES

Test sample	009A03	027A41	028A26	024A23
1	11333	12754	15352	14592
2	11338	12565	15414	14432
3	11400	12582	15359	14513
4	11343	12618	15350	14513
5	11334	12620	15342	14502
6	11435	12671	15421	14470
7	11339	12685	15382	14508
8	11382	12576	15368	14540
9	11268	12560	15312	14500
10	11386	12671	15297	14408

TABLE 4

THE HIT OR MISS COUNT OF PROBE IMAGES FOR TEN TIMES

S.No	Hit/Miss
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	0
10	1
(a) 009A03	

S.No	Hit/Miss
1	0
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
(b) 027A41	

S.No	Hit/Miss
1	0
2	0
3	0
4	0
5	0
6	0
7	0
8	0
9	0
10	0
(c) 028A26	

S.No	Hit/Miss
1	1
2	0
3	1
4	0
5	1
6	0
7	1
8	0
9	1
10	1
(d) 024A23	

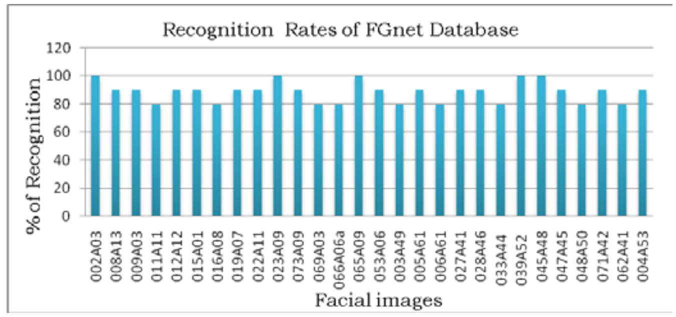

Fig. 9 Bar graph for successful recognition rates of FG-NET aging database

4. Conclusion

The present paper proposed a new method for face recognition and age classification based on MPP-1g on LDP. The novelty of the present approach is, it is rotationally, pose, noise, illumination invariant due to basic principles of LDP and the proposed MPP-g. The present paper outlines that one need not necessarily evaluate the frequency of occurrences of MPP-2g to MPP-8g for building an efficient face recognition system. The MPP-1g on LDP facial images effectively recognizes the facial images because MPP-1g contains more facial texture information. The present paper also outlines that MPP-1g and MPP-4g contains more textural and topological information of the facial skin, that is the reason these two texture features are classifying the child and adult.

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