Morphological Primitive Patterns with Grain Components on LDP for Child and Adult Age Classification

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ABSTRACT
Human beings can easily categorize a person's age group from an image of the person's face and are often able to be quite precise in this estimation. This ability has not been pursued in the computer vision community. To address this, the present paper proposes a novel local texture features on facial images that classify adult and child 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 proposed MPP-g is rotationally and pose invariant when compared to pattern trends that represents a shape. The experimental result on FGnet database images shows the efficacy of the proposed method.

Keywords
Morphological primitive patterns with grain components, Local Directional Pattern, local texture features, edge response values.

1. INTRODUCTION
Human facial image processing has been an active and interesting research issue for years. Since human faces provide a lot of information, many topics have drawn lots of attentions and thus have been studied intensively on face recognition [1]. Other research topics include predicting feature faces [2], reconstructing faces from some prescribed features [11], classifying gender, races and expressions from facial images [5], and so on. However, very few studies have been done on age classification. The ability to classify age from a facial image has not been pursued in computer vision. Facial aging has been an area of interest for decades [15, 16, 14, 13, 8], but it is only recently that efforts have been made to address problems like age estimation, age transformation, etc. from a computational point of view [10, 21, 11, 12, 17, 19, 20, 9, 18]. Age classification problem was first worked on by Kwon and Lobo [10]. Their study classfied input images as babies, young adults and senior adults based on cranio-facial development and skin wrinkle analysis. Yun et al. [6] used the database of human faces containing detailed age information to verify their proposed method, in which the spatial transformation of feature point was employed to express several age patterns with corresponding different ages. Each input facial image will be compared with age patterns to obtain the age estimation result. The recognition rate in an error range of 15 years was about 80%.

Burt and Perrett [8] created composite faces for different age groups by computing the average shape and texture of human faces that belong to each age group. Lanitis et al. [11] constructed an aging function based on a parametric model for human faces and performed automatic age progression, age estimation, face recognition across age etc. Lanitis et al. [12] compared the parametric model age estimation process with that of neural networks based approaches. Gandhi [3] designed a support vector machine based age estimation technique and extended the image based surface detail transfer approach to simulate aging effects on faces. Ramanathan and Chellappa [4] proposed a Bayesian age-difference classifier built on a probabilistic eigenspaces framework to perform face verification across age progression. Though the aforementioned approaches propose novel methods to address age progression in faces, in their formulation most approaches ignore the psychophysical evidences collected on age progression.

Even with the human eye, estimates of a candidate's age are often inaccurate. One of the reasons why age-group classification is difficult is that enormous time and expense is required for collecting images including a wide variety of age-groups under the same lighting conditions, due to privacy and portrait rights. The FGnet [7] contains images from a wide variety of lighting conditions and age-groups. In addition, the number of images under a particular lighting condition is unbalanced. To achieve accuracy in classification, a new framework that can reduce the influence of different lighting conditions, is essential before classification. Ahonen et al. [22] proposed Local Binary Pattern (LBP) that provides an illumination invariant description of face image. However, the existing methods still suffer much from non-monotonic illumination variation, random noise and change in pose, age and expression.

For this, the present paper identified Morphological primitive patterns with grain components (MPP-g) on a Local Directional Pattern (LDP) concept. The proposed method, which extracts the local texture features, overcomes the drawbacks of LBP and is more robust for age classification and face recognition. The local descriptor LDP considers the edge response values in all different directions instead of surrounding neighboring 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 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 [23], which overcomes the drawbacks of LBP and is more robust for age classification and face recognition. The local descriptor LDP considers the edge response values in all different directions instead of surrounding neighboring 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 [24]. It labels each pixel of an image by thresholding its *P*-neighbor values with the center value by converting the result into a binary number by using Equation 1.

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{p-1} s(g_p - g_c)2^p,$$

$$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (1)$$

where g_c denotes the gray value of the center pixel (x_c, y_c) and g_p corresponds to the gray values of P equally spaced pixels on the circumference of a circle with radius R.

Ojala et al. [24] 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. [22] 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, as explained in section 2.2. 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 2.2.

Step 3: The proposed MPP-1g to MPP-8g are evaluated on LDP for age classification as explained in 2.3.

Step 4: Based on the frequency of occurrences of MPP-1g to MPP-8g age classification algorithm is performed.

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, LDP calculates 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.

$$\begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix}$$

(M_0) (M_1) (M_2) (M_3)

$$\begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix}$$

(M_4) (M_5) (M_6) (M_7)

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	48

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

85	32	26
53	50	10
60	38	48

LBP=0010**0**1000
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 mask. This makes the present method as rotationally and poses invariant. Frequency occurrences of grain components MPP-g in the present paper is 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.. The frequency of occurrences of MPP-1g to MPP-8g are computed by the proposed Algorithm 1 on a 3×3 non overlapped mask of LDP facial texture images, and stored in the facial database.

3. RESULTS AND DISCUSSIONS

To show the significance of the proposed novel method the present paper has evaluated MPP-1g to MPP-8g on LDP for child and adult facial images from different poses of FGnet aging database of 1002 images. The Fig.6 and Fig.7 shows 15 child and 13 adult facial images with different poses of FGnet aging database respectively.

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.

The present paper assumed that the childhood begins from 0 to 15 years and adulthood is above 40 years. The Table 1 and Table 2 indicate the frequency of occurrences of MPP-g for sample database of FGnet.

Table 1. Frequency of occurrences of a child facial images using MPP-g

Child images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
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 a 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 inbetween 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.

Table 3. Frequency of occurrence of MPP-g with 30^0 rotation on LDP for Child Facial Images

Child images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
002A03	16924	867	652	842	994	1039	527	20343
008A13	14076	1446	1075	1169	1196	1351	717	19158
009A03	11366	999	778	999	1179	1571	1038	17023
011A11	9763	594	518	663	673	837	364	12336
012A12	9028	747	557	703	765	697	295	11841
015A01	13362	1610	1277	1145	2333	4063	2002	25244
016A08	14494	926	775	932	1199	2376	2624	31622
019A07	6244	700	724	1010	1349	2701	2439	17932
022A11	15827	809	552	637	774	921	520	18924
023A09	16119	1283	878	938	889	1114	574	20005
073A09	6211	1044	1084	1138	2230	4553	3884	22269
069A03	8406	1164	1217	1004	2370	4015	2722	21617
066A06a	14395	965	741	992	1268	1852	1123	20056
065A09	7129	554	507	617	756	1405	1371	30261
053A06	11842	495	461	743	982	2131	2062	24097

Table 4. Frequency of occurrence of MPP-g with 30^0 rotation on LDP for Adult Facial Images

Adult images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
003A49	20056	1182	888	1296	1155	910	295	24098
005A61	19532	1096	835	1246	1008	1110	419	24834
006A61	15667	848	694	1967	1274	1972	1070	27388
027A41	12673	1708	1517	1942	2371	3195	1629	24845
028A46	15659	931	803	1999	1343	1957	1267	26921
033A44	15629	1249	997	1339	1530	1716	603	26817
039A52	16644	2406	2114	2318	2624	2726	1227	27725
045A48	20393	1211	980	1399	1255	1280	580	30986
047A45	12470	1541	1540	1850	2327	3704	3038	31314
048A50	19460	827	652	1823	1034	1326	670	32992
071A42	16764	1152	995	1213	1471	1905	943	33341
062A41	10534	2108	1832	2285	2930	3372	1600	33123
004A53	13130	1694	1317	1607	1783	1973	957	35323

Table 5. Frequency of occurrence of MPP-g with 45^0 rotation on LDP for Child Facial Images

Child images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
002A03	16892	905	691	813	933	1156	688	22866
008A13	13991	1515	1121	1181	1126	1439	896	21995
009A03	11298	1070	829	1013	1062	1688	1054	19235
011A11	9597	701	535	579	601	1001	289	14586
012A12	8991	754	630	735	642	757	418	13642
015A01	13366	1678	1397	1183	2153	4102	2023	29094
016A08	14468	969	837	981	1176	2449	2552	35617
019A07	6198	700	740	1035	1347	2835	2409	20080
022A11	15663	824	609	665	742	1053	466	21594
023A09	16060	1310	873	914	864	1145	746	23032
073A09	6128	1107	1183	1194	2169	4655	3851	25538
069A03	8410	1283	1294	1035	2210	4167	2781	24345
066A06a	14332	986	826	1065	1115	1983	1184	23030
065A09	7009	632	554	618	736	1558	1359	33759
053A06	11804	525	526	757	901	2249	2168	27295

Table 6. Frequency of occurrence of MPP-g with 45^0 rotation on LDP for Adult Facial Images

Adult images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
003A49	19959	1429	1074	1212	1080	958	271	27478
005A61	19365	1154	923	1315	952	1138	424	26558
006A61	14902	870	756	1921	1112	2005	1268	23110
027A41	12570	1755	1652	1913	2284	3218	1652	27397
028A46	12337	676	586	1672	783	1562	697	18408
033A44	14978	1281	1027	1296	1256	1668	774	23089
039A52	16561	2649	2232	2278	2400	2728	1418	31735
045A48	17766	935	718	1811	776	1094	553	24003
047A45	12026	1378	1430	1714	2157	3618	2918	29048
048A50	18524	578	505	1624	690	1064	716	23524
071A42	15887	1009	809	1949	1032	1739	849	23095
062A41	9607	1860	1652	2043	2516	3233	1477	23837
004A53	11962	1454	1083	1356	1182	1652	582	19738

Table 7. Frequency of occurrence of MPP-g with 135^0 rotation on LDP for Child Facial Images

Child images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
002A03	16908	857	758	940	889	1108	574	22910
008A13	14038	1642	1104	1144	1129	1426	595	22186
009A03	11282	1149	856	956	1061	1651	1056	19238
011A11	9605	665	550	613	582	962	327	14585
012A12	9022	757	651	693	644	788	369	13645
015A01	13230	1650	1475	700	2120	3777	2491	29253
016A08	14458	1012	832	948	1177	2483	2532	35607
019A07	6239	744	744	1014	1435	2865	2362	19941
022A11	15688	1292	894	873	900	1173	652	23040
023A09	16120	1098	1201	1175	2164	4652	3839	25542
073A09	6154	1259	1315	1058	2254	4164	2819	24337
069A03	8419	1259	1315	1058	2254	4164	2819	24337
066A06a	14332	1020	787	1017	1146	2058	1140	23021
065A09	7009	639	570	613	723	1543	1367	33761
053A06	11791	554	529	721	917	2219	2208	27286

Table 8. Frequency of occurrence of MPP-g with 135^0 rotation on LDP for Adult Facial Images

Adult images	MPP-1g	MPP-2g	MPP-3g	MPP-4g	MPP-5g	MPP-6g	MPP-7g	MPP-8g
003A49	19992	1397	1075	1271	1029	992	231	27474
005A61	19342	1190	896	1216	974	1169	390	26552
006A61	14873	844	734	1980	1070	2022	939	23482
027A41	12501	1860	1678	1935	2225	3188	1702	27352
028A46	12275	671	574	1638	802	1461	1004	18296
033A44	14915	1309	1035	1306	1262	1582	591	23469
039A52	16425	2528	2377	2324	2395	2787	1027	32138
045A48	18027	922	715	1828	798	1069	495	23802
047A45	12059	1441	1448	1760	2056	3737	2908	28880
048A50	18520	588	511	1628	672	1057	736	23513
071A42	15819	978	835	1922	1021	1739	617	23438
062A41	9606	1831	1709	2103	2344	3407	1405	23820
004A53	11953	1389	1058	1262	1163	1659	590	19735

4. CONCLUSIONS

The present paper proposed a new method for age classification of child and adults based on the MPP-g on LDP in the facial skin. 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, Mpp-3g and Mpp-5g to MPP-8g for the age classification. The 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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