Age Classification based on Corner Pixel Grey Level Co-Occurrences Matrix (CP-GLCM) of TN-LBP

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ABSTRACT
The present paper proposes a novel scheme based on third order neighbourhood LBP (TN-LBP). The present paper observed and noted that the TN-LBP forms two types of corner pixels i.e. top corner and bottom corner pixels. The present paper derived Grey Level Co-occurrence Matrix (GLCM) based on LBP values of Top Corner Pixels (TCP) of TN-LBP and Bottom Corner Pixels (BCP) of TN-LBP. On this GLCM features are derived. Based on these features human age is classified in to child (0 to 12 years) young adult (13 to 30 years), middle age (31 to 50 years) and senior age (above 60 years).

General Terms
Classification, Image Processing et. al.

Keywords
Age Classification, Local Binary Pattern (LBP). Third Order Neighborhood, Corner Pixel Grey Level Co-occurrence Matrix (CP-GLCM)

1. INTRODUCTION
A human face comprises of lot of information, and they can used in various applications like face recognition [3], age group classification [2]. Lot of research is undergoing in the area of human facial image processing and it is still active and interesting. The other research areas include predicting feature faces [4], reconstructing faces from some prescribed features [5], classifying gender, races, and expressions from facial images [6], and so on. On age group classification/estimation much less work has been done, but several applications such as enforcement of law in usage of certain types of drug and entertainment scenarios, targeted advertisements etc require require age group classification/estimation. Several applications are under development in the area of human communication to achieve automatic identification of individuals using computers.

Wen-Bing Horng, Cheng-Ping Lee and Chun-Wen Chen et.al [2] considered four age groups for classification, including babies, young adults, middle-aged adults, and old adults. This is implemented based on the symmetry of human faces and the variation of gray levels, the positions of eyes, noses, and mouths are located by applying the Sobel edge operator and region labeling in the above methods. Kwon et. al. [7] implemented age classification on facial images is based on cranio-facial development theory and skin wrinkle analysis in which only three age-groups babies, young adults, and senior adults.

Various age group classification method are implemented to classify facial images into various age groups i.e. babies and adults [8], two age groups 20-39 and 40-49 [9]. In addition to this classification of facial images based on sex [9, 10] are also implemented. Sasikiran et.al. [11] implemented age classification by reducing the image dimensionality and classified the human age into five categories. The above method is extended based on the topological texture features of the facial skin for an effective age classification that classified the human age into five groups [12]. Various age classification methods based on LBP are also proposed [14, 15] and a pattern based dimensionality reduction model for age classification is also proposed recently and classified age groups effectively into four groups [13].. The present paper attempted to classify the age groups into four categories based on Corner Pixel Grey Level Co-occurrence Matrix (CP-GLCM) features extracted on TN-LBP on the facial image.

2. DERIVATION OF CORNER PIXEL GREY LEVEL CO-OCCURRENCES MATRIX (CP-GLCM) OF TN-LBP
The proposed method evaluated GLCM features on TCP (Top Corner pixels) and BCP (Bottom Corner Pixels) of TN-LBP. The proposed method based T-TN-LBP consists of 9 steps as described below.

Step 1: Take facial image as Input Image (Img).

Step 2: Convert the RGB image into Grey scale Image by using HSV color model.

Step 3: Crop the grey scale image.

Step 4: The present research evaluated TN-LBP on each 5 x 5 sub image. The TN contains only 13 pixels of 25 pixels of 5x5 neighborhoods as shown in Fig.1. The TN-LBP grey level sub image is converted into binary sub image by comparing the each pixel of TN grey level sub image with the mean value of TN grey sub image. The following Eqn.1 is used for grey level to binary conversion.

$$\text{TN-P}_i = \begin{Bmatrix} 0 & \text{if} & P_i < V_0 \\ 1 & \text{if} & P_i \geq V_0 \end{Bmatrix} \text{ for } i = 1, 2, ..13 \qquad (1)$$

Where V_0 is the mean of the TN matrix.

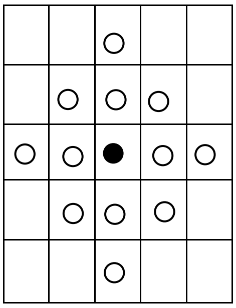

Fig. 1: Third Order Neighborhood for a central pixel.

Step 5: The interesting thing in TN-LBP is it will have two corner pixel patterns. The present research named them as TCP and BCP. Both TCP and BCP will have four pixels only. TCP of TN-LBP is indicated by green color and BCP of TN-LBP are indicated by sky blue color in the Fig.2. The Pixels P1, P5, P13 and P9 form TCP of TN-LBP and the pixels P3, P6, P8 and P11 forms BCP of TN-LBP.

		P1		
	P2	P3	P4	
P5	P6	P7	P8	P9
	P10	P11	P12	
		P13		

Fig. 2: Considered diamond patterns.

Step 6: LBP code is evaluated on the TCP and BCP of TN-LBP. To achieve rotational invariance the minimum code is taken. The LBP code ranges from 0 to 15.

Step 7: The Corner Pixel Grey Level Co-occurrence Matrix (CP-GLCM) of TN-LBP is generated by representing the TCP- pattern values on X- axis and BCP-pattern values on Y-axis. This method has the elements of relative frequencies in both patterns, since the LBP code values of these patterns i.e. TCP and BCP ranges from 0 to 15. That is the reason the CP-GLCM of TN-LBP have a fixed size of 16×16 because of number of distinct values in this method is 16.

Step 8: Extract the contrast, correlation, homogeneity and energy features on CP-GLCM of TN-LBP.

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

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

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

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

Step 9: Based on four feature values facial image is classified as one of the category (Child Age(0-12), Young Age(13-30), Middle Age(31-50) and Senior Age (51 -70).

3. RESULTS AND DISCUSSIONS

In implementing this a database is established by collecting 1002 facial images from FG-NET database, 500 images from Google database and other 600 images from the scanned photograph which results in a total of 2102 sample facial images. In the proposed method the sample images are grouped into four age groups of Child age(0-12), Young Age(13-30), Middle Age(31-50) and Senior Age (51 -70). A few of them are shown in Fig.3. The statistical features are extracted from CP-GLCM of TN-LBP for different facial images and the results are stored in the feature database. Feature set leads to representation of the training set. The statistical features of four age groups of facial images are shown in tables 1, 2, 3, and 4 respectively. Based on the derived features on CP-GLCM of TN-LBP an algorithm is derived by the present research to classify the facial image into one of the category of Child age(0-12), Young Age(13-30), Middle Age(31-50) and Senior Age (51 -70).

To evaluate the efficacy of the proposed method various facial images are considered and CPCM of TN-LBP is evaluated and derived the GLCM features on them. Based on the proposed age classification algorithm the age classification rate of the test images is established and noted in table 5.

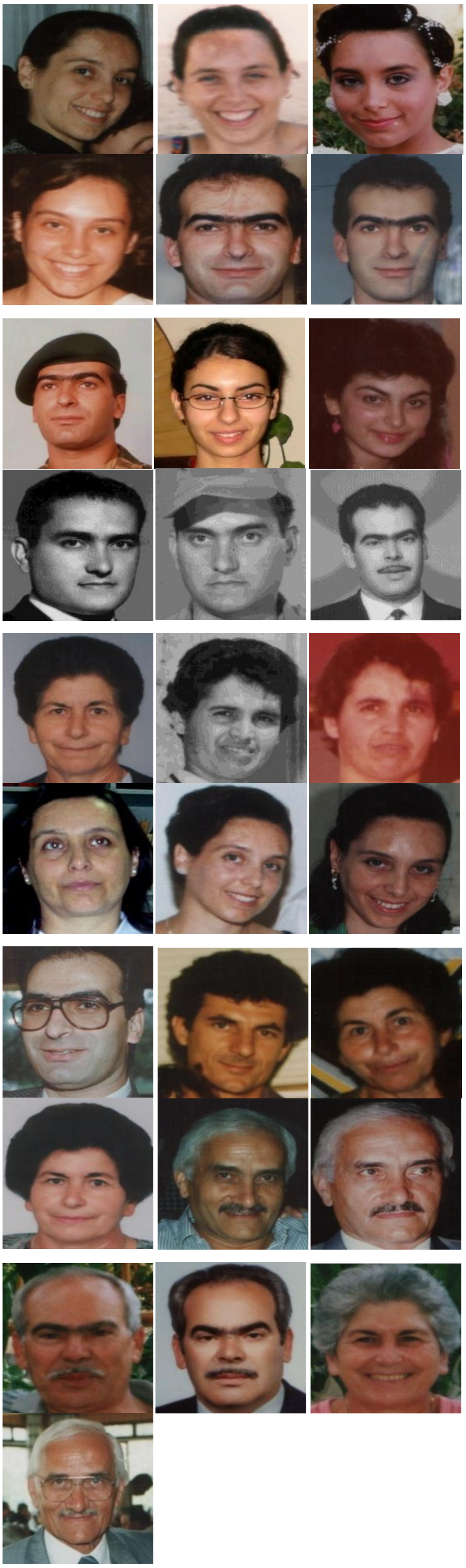

Figure 3: FGNET aging database: 011A07, 011A05, 010A10, 010A09, 010A07b, 001A14, 019A07, 009A14, 009A13, 009A11, 008A16, 008A13, 010A05, 010A04, 010A01, 009A09, 009A05, 004A21, 002A29, 002A26, 002A23, 002A21, 001A29, 001A28, 001A22, 009A22a, 008A21, 004A28, 004A26, 006A36, 005A40, 011A40, 001A43b, 002A31, 001A33 007A37, 005A52, 005A49, 004A53, 004A51, 048A54 , 006A61, 005A61, 004A63.

Table 1: Feature set values of Child Age images.

S. No	Image Name	Contrast	Correla-tion	Energy	Homog-eneity
1	001A02	17.551	0.838	0.034	0.62953
2	001A05	15.478	0.859	0.042	0.66238
3	001A08	20.72	0.81	0.021	0.57649
4	001A10	24.445	0.613	0.023	0.53384
5	002A03	20.61	0.742	0.032	0.59142
6	002A04	23.384	0.652	0.03	0.56721
7	002A07	30.176	0.511	0.01	0.42063
8	008A06	21.905	0.752	0.02	0.5537
9	009A00	19.417	0.789	0.032	0.60454
10	010A01	19.347	0.746	0.029	0.57398
11	010A09	22.9	0.709	0.023	0.55456
12	024A05	27.495	0.539	0.013	0.45444
13	024A10	22.704	0.695	0.019	0.52015
14	025A00	12.626	0.967	0.05	0.70013
15	025A03	25.133	0.59	0.018	0.49319
16	025A07	26.681	0.558	0.016	0.48478
17	002A12	19.234	0.756	0.036	0.60803
18	009A11	16.487	0.9	0.03	0.64593
19	025A12	21.091	0.706	0.029	0.56771
20	026A11	23.454	0.669	0.021	0.53242

Table 2 :Feature set values of Young Age images.

S. No	Image Name	Contrast	Correla -tion	Energy	Homog-eneity
1	001A22	22.847	0.456	0.02	0.263
2	001A28	29.051	0.526	0.026	0.314
3	001A29	22.198	0.414	0.023	0.257
4	003A23	28.624	0.497	0.031	0.311
5	003A25	21.822	0.451	0.021	0.261
6	012A21	25.679	0.285	0.014	0.169
7	012A23	21.046	0.444	0.027	0.282
8	012A24	22.977	0.352	0.02	0.222
9	012A26	20.086	0.481	0.026	0.294
10	012A27	28.563	0.505	0.033	0.218
11	012A30	23.719	0.354	0.018	0.205
12	024A23	22.342	0.413	0.023	0.247
13	024A25	25.202	0.343	0.018	0.205
14	027A22	25.297	0.296	0.016	0.181
15	027A25	27.468	0.267	0.01	0.13
16	027A30	22.272	0.403	0.023	0.246
17	047A23	23.665	0.315	0.03	0.264
18	047A27	29.253	0.455	0.029	0.287
19	048A30	27.441	0.269	0.014	0.165
20	001A14	27.34	0.57	0.03	0.332
21	001A16	32.474	0.182	0.012	0.128
22	001A18	22.139	0.417	0.025	0.27
23	001A19	28.197	0.235	0.015	0.174
24	002A15	23.684	0.349	0.023	0.24
25	009A13	27.407	0.269	0.013	0.153
26	011A17	21.587	0.436	0.024	0.261
27	011A20	29.685	0.469	0.029	0.298
28	025A15	26.285	0.307	0.015	0.17
29	025A18	24.958	0.316	0.017	0.195
30	025A19	23.555	0.386	0.021	0.233

Table 3: Feature set values of Middle Age images.

S. No	Image Name	Contrast	Correla -tion	Energy	Homog-eneity
1	001A33	19.805	0.367	0.019	0.53
2	001A40	18.09	0.469	0.019	0.582
3	002A31	14.002	0.37	0.018	0.513
4	003A35	16.716	0.592	0.02	0.638
5	003A38	17.139	0.547	0.014	0.631
6	012A32	13.988	0.345	0.017	0.495
7	013A34	15.485	0.318	0.016	0.494
8	018A33	18.772	0.471	0.018	0.616
9	018A34	17.837	0.492	0.021	0.593
10	019A37	18.586	0.393	0.015	0.549
11	020A36	17.882	0.482	0.014	0.573
12	021A35	17.004	0.288	0.012	0.447
13	021A39	16.601	0.277	0.011	0.448
14	025A34	17.18	0.243	0.012	0.445
15	025A39	19.233	0.151	0.008	0.387
16	039A35	16.244	0.268	0.015	0.47
17	047A33	15.747	0.405	0.021	0.575
18	001A43a	15.886	0.316	0.018	0.531
19	003A47	19.327	0.498	0.019	0.597
20	003A49	19.582	0.485	0.019	0.601
21	004A48	18.211	0.495	0.018	0.591
22	005A45	10.867	0.459	0.018	0.578
23	006A42	13.81	0.365	0.02	0.541
24	013A41	12.486	0.4	0.018	0.549
25	013A44	13.879	0.372	0.019	0.524
26	022A50	13.698	0.346	0.019	0.507
27	028A46	15.795	0.316	0.02	0.54
28	039A45	19.97	0.442	0.018	0.569
29	039A50	14.547	0.336	0.011	0.516
30	047A45	18.947	0.247	0.011	0.428

Table 4: Feature set values of Senior Age images.

S. No	Image Name	Contrast	Corre-lation	Energy	Homogeneity
1	003A51	22.901	0.4314	0.0207	0.5557
2	003A57	21.446	0.4721	0.0359	0.6277
3	003A58	21.446	0.4317	0.0393	0.6212
4	003A59	20.446	0.4993	0.037	0.6807
5	003A60	24.376	0.3824	0.0186	0.5219
6	004A53	20.855	0.4928	0.0277	0.5978
7	006A54	23.698	0.4002	0.0194	0.5317
8	006A55	23.698	0.4002	0.0194	0.5317
9	006A56	23.698	0.4002	0.0194	0.5317
10	039A52	24.426	0.3321	0.0182	0.5005
11	047A55	23.694	0.3840	0.0214	0.5346
12	004A62	22.667	0.4134	0.0213	0.5486
13	004A63	20.642	0.4964	0.0265	0.607
14	006A61	22.381	0.3727	0.0263	0.5651
15	006A67	21.31	0.4640	0.0331	0.6038
16	006A69	24.803	0.3712	0.018	0.5221
17	045A64	21.326	0.4285	0.0266	0.5596
18	045A65	20.667	0.4000	0.0327	0.5879
19	045A66	20.297	0.4421	0.0345	0.6012
20	069A52	22.426	0.3321	0.0172	0.5005

From the above tables derive an algorithm to classify the facial image into one of the category of Child age(0-12), Young Age(13-30), Middle Age(31-50) and Senior Age (51 - 70).

Algorithm 1: Age group classification based on features derived from CP-GLCM of TN-LBP

START

if Contrast > 20 and Homogeneity > 0.5

print(" Facial image is Senior Age (51-70)")

else if Contrast < 20 and energy < 0.022

print(" Facial image is Middle Age (31-50)")

else if Contrast > 20 and Homogeneity < 0.5

print(" Facial image is Young Age (13-30)")

else if Correlation > 0.5

print(" Facial image is child Age (0-12)")

else

print(" Facial image is unknown age group")

END

4. COMPARISON OF THE PROPOSED METHOD WITH OTHER EXISTING METHODS

The proposed method of age classification is compared with the existing methods [1, 2]. The method proposed by M. Yazdi et.al [1] classified age group using RBF Neural Network Classifier. The age group classification method proposed by Wen-Bing Horng is based on two geometric features and three wrinkle features of facial image. The percentage of classification of proposed method and other existing methods are listed in table 6. The graphical representation of the percentage mean classification rate for the proposed method and other existing methods are shown in Fig. 4.

Table 6: Classification rate of the proposed method with other existing methods.

Image Dataset	Existing age classification method [1]	Existing age classification method [2]	Proposed Method
FG-NET	89.67	90.52	100
Google	85.3	81.58	95
Scanned	88.72	85.42	93.5
Average	87.9	85.84	96.17

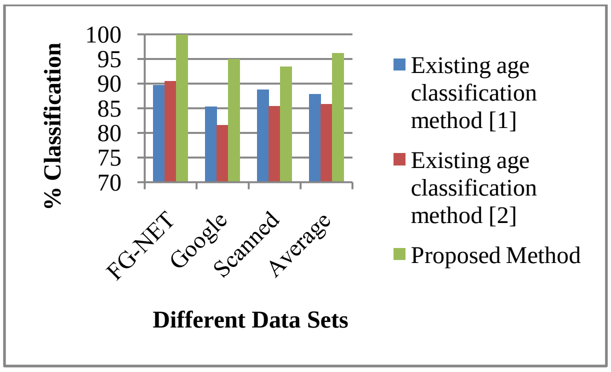

Figure 4: Classification chart of proposed method and other existing methods.

5. CONCLUSIONS

The proposed method estimated the relationship between the Top (outer) and Bottom (inner) corner pixels of TN-LBP. The bottom or inner corner pixels are connected and the top or outer corner pixels of TN-LBP are not connected. The proposed method present in this paper successively utilized the TN-LBP by reducing the complexity in establishing the LBP code for 13 pixels i.e. ranges from 0 to 2^{13}-1. The proposed CP-GLCM of TN-LBP achieved a good classification rate when compared to the existing method.

Table 5. Test set results of different dataset images.

Sno	Image Name	Contrast	Correlation	Energy	Homogeneity	Group	Result
1	gogle_im_01	25.202	0.5426	0.018	0.2049	Middle	Success
2	gogle_im_02	21.704	0.5945	0.019	0.5101	Child	Success
3	gogle_im_03	26.086	0.4806	0.026	0.2943	Young	Success
4	gogle_im_04	22.384	0.7519	0.03	0.5872	Child	Success
5	gogle_im_05	10.867	0.4975	0.019	0.5969	Middle	Success
6	gogle_im_06	23.694	0.3713	0.018	0.5221	Senior	Success
7	gogle_im_07	19.582	0.4853	0.019	0.6013	Middle	Success
8	gogle_im_08	21.326	0.4641	0.033	0.6038	Senior	Success
9	gogle_im_09	24.563	0.5054	0.033	0.4179	Young	Success
10	gogle_im_10	25.719	0.3542	0.018	0.4053	Young	Success
11	076A14	26.342	0.4131	0.023	0.3466	Young	Success
12	077A00	19.487	0.79	0.03	0.6459	Child	Success
13	082A20	24.803	0.3727	0.026	0.5651	Young	Success
14	082A25	22.086	0.4806	0.026	0.2943	Young	Success
15	067A33	15.886	0.3163	0.018	0.5306	Middle	Success
16	067A39	13.81	0.4593	0.018	0.5782	Middle	Success
17	048A52	19.327	0.3648	0.02	0.5413	Middle	Success
18	048A54	21.31	0.4965	0.027	0.607	Senior	Success
19	067A48	29.233	0.4046	0.021	0.5752	Middle	Fail
20	048A65	20.905	0.7519	0.02	0.5537	Child	Success
21	sca.img-001	20.681	0.5576	0.016	0.4848	Child	Success
22	sca.img-002	20.046	0.4442	0.027	0.3224	Young	Success
23	sca.img-003	22.667	0.4286	0.027	0.5596	Senior	Success
24	sca.img-004	22.977	0.352	0.02	0.3124	Young	Success
25	sca.img-005	20.642	0.3841	0.021	0.5346	Senior	Success
26	sca.img-006	22.381	0.4134	0.021	0.5486	Senior	Success
27	sca.img-007	16.244	0.1508	0.008	0.3875	Middle	Success
28	sca.img-008	15.747	0.2682	0.015	0.4695	Middle	Success
29	sca.img-009	18.679	0.285	0.014	0.469	Young	Fail
30	sca.img-010	12.626	0.8667	0.05	0.7001	Child	Success

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