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Age Classification of Facial Images Using Third Order Neighbourhood Local Binary Pattern

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Abstract -The present paper extends the concept of second order neighbourhood LBP to third order neighbourhood (TN)LBP (TN-LBP). The TN contains 12 neighboring pixels formed on a 5 x 5 window. One of the difficulties in considering TN-LBP is its huge number of patterns. To addressthis present paper divided the TN-LBP into two groups of 4-pixels each, i.e. top corner and bottom corner and each of them consists of 16 patterns only. The present paper intelligently derived uniform and non-uniform patterns on the top and bottom corner pixels of TN-LBP. 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) on the FG-net database. The experimental results indicate the efficiency of the proposed method over the existing methods.
Key words: Third order Neighborhood, Uniform local binary pattern, Non uniform local binary pattern.

1. Introduction

The human face contains a great deal of information related to personal characteristics, including identification, emotion, age, gender and race. This information has been used extensively in the face-based human–computer interaction (HCI) systems capable of interpreting the facial information found in human-to human communication [1]. Currently, the research related on age estimation using face images is more important than ever, because it has many applications, such as an internet access control, underage cigarette-vending machine use [1,2], age-based retrieval of face images [2], and age prediction systems for finding lost children and face recognition robust to age progression. In addition, the estimated age of consumers who look at billboards is used in age specific target advertising as consumer preferences differ greatly by age. Age estimation systems are generally designed to use two steps: an aging feature extraction and a feature classification. Feature extraction is very important in age estimation, since the extracted features greatly affect the classification performance. For this reason, a great deal of effort has been directed towards the extraction of discriminative aging features. These features can be categorized into local and global features, and hybrid features, which are a combination of the global and local features. Local features consist of the amount and depth of wrinkles; skin aging using freckles and age spots, hair color and the geometry of facial components. The local features have been commonly used to classify people into age groups (e.g. babies, young adults and senior adults) as they possess unique characteristics that distinguish specific age groups. For example, wrinkles are found in adulthood rather than in childhood, and geometric features, such as the distance ratios between features such as the eyes, the end of the nose, and the corners of the mouth, are noticeably changed in childhood rather than in adulthood. Consequently, these features are better suited to applications requiring an age group classification (e.g. the class of less than 20 years old, the class of 20–39 years old, etc.) rather than a detailed age estimation (e.g. 17, 23 years old, etc.).

The feature classification can be divided into three approaches: the age group classification [6, 9, 10, 12], the single level age estimation [2, 3, 7, 8, 11] and the hierarchical age estimation [2, 4, 5]. Age group classification is an approach that roughly predicts an age group, whereas single-level and hierarchical age estimations are focused on detailed age prediction. The single-level age estimation is to find the age label in the total data set. On the other hand, the hierarchical age estimation is a coarse-to-fine method used to find the age label in a pre-classified group's small data set. Of these methods, the hierarchical age estimation provides the most improved performance [2, 4, 5]. As facial aging is perceived differently in different age groups, age estimation in a specific age group provides a more accurate result. Moreover age estimation on a smaller age group simplifies the computational load [4]. As mentioned above, the hybrid features and the hierarchical classifier provide a good performance for the estimation of age. However, they have been studied independently; research of different ordered LBP with statistical measurements has not been conducted in the previous works.

The non-parametric local binary pattern (LBP) operator was first mentioned by Harwood et al. [13] and then introduced to image texture description by Ojala et al. [14] for texture analysis. The operator enjoys some attractive properties such as tolerance to monotonic gray-scale, illumination variations, and computational simplicity, and has been demonstrated to be highly discriminative [15]. Due to these properties, it considerably successfully is used to textures analysis [16–23]. Recently many researchers worked various classification methods i.e. age, face and facial expressions by integrating LBP based on 2nd and 3rd order neighborhoods with statistical measures [14] and they achieved significant results by reducing the overall dimensionality.

In order to rather serve to real tasks, the original LBP operator [13, 14] with the 3x3 neighborhood is extended to different-size of neighborhoods and uniform pattern versions [15, 24]. The LBP operator has recently been used to face description [25–35] by adopting the region-division and concatenation histogram strategy. The spatially enhanced LBP histogram (eLBPH) is the first LBP-based face recognition(FR) approach(eLBPH for short here after) [25, 26], which divides a full facial image into some regions (subimages),then extracts a regional LBP histogram from each region and finally concatenates all regional histograms into a single global histogram as a face representation for recognition. The eLBPH methodology has permeated into many face analysis domains including face recognition [28–33], facial expression recognition [34, 35,46,46], gender recognition [36], face detection [37,47], face authentication [38–40], shape location [41,42,43] and soon. More-over, the boosting extension of eLBPH has also been utilized in the Beijing Olympics 2008 for identifying visitors [2031, 2032]. It has been reported that eLBPH is more effective than the naïve holistic LBP.The present paper identified most sensitive problems [37, 44] which influence the age classification and resolved with using incremental orders of LBP. The limitations of eLBPH are discussed and rectified using eminent features of LBP.

The present paper is organized as follows. The section 2 describes about different neighbourhoodsand section 3 describes about uniform and non-uniform LBP. The section 4 describes the proposed methodology, section 5 and section 6 gives the results and discussion and conclusions respectively.

2. Different Orders of Neighborhood

Imaging understanding is one of the most important tasks involving a classification system. Its primary purpose is to extract information from the images to allow the discrimination among different objects of interest. The classification process is usually based on grey level intensity, colour, shape or texture. Image classificationand analysis is of great interest in a variety of applications, starting from pattern recognition and multispectral scanner images obtained from aircraft or satellite platforms for microscopic images of cell cultures or tissue samples and also in various big data analytics.

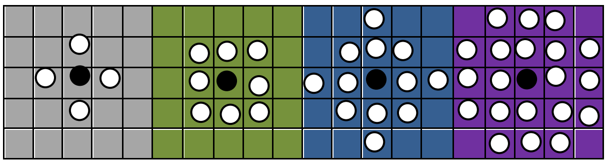

Fig.1: Neighborhood for a central pixel: (a) First order (b) Second order (c) Third order (d) Fourth order.

Most of the image analysis problems are related to the neighborhood properties i.e. edge detection, segmentation, dilation, closing, opening, LBP, Texture Unit (TU), etc. Each pixel in a neighborhood or image is considered as a random variable, x_r, which can assume values $x_r \in \{0, 1\ldots G\}$, where G is the number of grey levels of the image. The probability P ($x_r = x_r | r$), where r is the neighbor set for the element x_r. The Fig.1 illustrates different orders of neighborhood for a central pixel. Most of the research involved in image processing is mostly revolved around first and second order neighborhood only. This is because all the 4-pixels in a 2 x 2 neighborhood and 8- neighboring pixels on a 3 x 3 neighborhoodare well connected with central pixels. On the first and second order neighborhoods the neighboring pixels will have distance of 1 or 1.44 with the central pixel. This means they are immediate neighbors to the central pixel with in horizontal or vertical or diagonal side. The methods based on second and first order neighborhood are given extraordinary results in various issues. The present paper considers the difficulties and complexities involved in the third order neighborhood and derive a new, simple and efficient model for age classification.

The third order neighborhood is defined on a 5 x 5 window and it consists of 13 pixels including centre pixel as shown in Fig.1.c and fourth order neighbourhood also derived on 5 x 5 neighborhood and it consists of 21 pixels as shown in Fig.1d. In the third and fourth order all the neighboring pixels are not immediate neighbors to the central pixel and they will form a distance from 1 to 3 with central pixel.

3. Uniform and Non-Uniform Patterns on LBP

The '*Local Binary Pattern'* (LBP) operator, first introduced by Ojala et al. [74], is a robust but theoretically and computationally simple approach for texture analysis. It brings together the separate statistical and structural approaches to texture analysis of both stochastic micro textures and deterministic macro textures simultaneously.To overcome the consideration of huge number of LBP i.e 0 to 255.Ojala et.al [59]derived uniform LBP (ULBP) and non-uniform LBP (NULBP) on LBP.

A pattern is considered 'uniform' (U) if the number of transactions in the sequence between 0 and 1 is less than or equal to two. It was observed by Ojala et al. [59], [60] that certain patterns seem to be fundamental properties of texture, these patterns are called ''uniform'' because they have at most two one-to-zero or zero-to-one transitions in the circular binary code defined in equation 1. That is, the larger the uniformity value U is, the more likely is that spatial transition occurs in the local pattern.

$$U(LBP_{P,R}) = |s(q_{P-1} - q_c) - s(q_0 - q_c)| + \sum_{P=1}^{P-1} |s(q_P - q_c) - s(q_{P-1} - q_c)| \quad (1)$$

For example, patterns 0 (bitwise 00000000) and 255 (bitwise 11111111) have a U value of 0 while patterns 1, 2, 4, 8, 16, 32, 64 and 128 (bitwise 00000001, 00000010, etc.) have a U value of 2 as there are exactly two 0/1 or 1/0 transitions in the bitwise representation. Similarly, patterns 00000011, 00000111, 00001111, 00011111, 00111111, 01111111 and other circularly rotated bitwise rotated versions have a U value of 2. Finally, patterns of (00000000, 00000001, 00000011, 00000111, 00001111, 00011111, 00111111, 01111111 11111111) and their circularly rotated versions of transformation invariant analysis have a U value of 2. These nine patterns correspond to p×(p-1)+3 distinct output values (i.e., 58 of 3×3 neighbourhood) of the 2^P un-rotated patterns that can occur in the 3×3 neighbourhood.

In practice, all the non-uniform patterns (U>2) are grouped under a ‘‘miscellaneous’’ label, while each uniform LBP is cast into a unique histogram bin according to its decimal value. This is because most of the local binary patterns in natural images are uniform. Ojala et al. [59] noticed that in their experiments with texture images, uniform patterns account for a bit less than 90% of all patterns when using the (8, 1) neighborhood and for around 70% in the (16, 2) neighborhood. In experiments with facial images [8] it was found that 90.6% of the patterns in the (8, 1) neighborhood and 85.2% of the patterns in the (8, 2) neighborhood are uniform.Merging all non-uniform patterns into one pattern (as done in the traditional LBP) or some limited patterns (as done in Hui Zhou et al., 2008 [36]) do not describe the stochastic characteristics of texture efficiently. As a result, texture primitive information represented by these patterns is lost, especially when large neighborhoods are considered. This single pattern makes the uniform patterns sensitive to noise. A further improvement of this classical LBP operator [6], [54] is to make efficient use of non-uniform patterns in an appropriate way. Several attempts were made to use non-uniform patterns and overcome this limitation of the standard LBP (Heikkila et al., 2009 [32]; Zhou et al., 2008 [36]; Liao et al., 2009 [51]). Heikkila et al. (2009) [32] and Liao etal (2007) [52] extracted rotation invariant non-uniform patterns. A TN-LBP has 12 sampling points. Therefore it generates p x (p-1) + 3 = 135 uniform patterns and 3961 non-uniform patterns. These figures show a huge number of non-uniform patterns and a large number of uniform patterns. In the same way it will have 243 uniform patterns for neighbourhoods of 16 sampling points.

4. Derivation ofTDP and BDP of TN-LBP

The proposed method evaluated transitions on third order neighbourhood LBP and derived a method for age classification with 7 steps as given below.

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

Step 2: Convert the colour 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 by including central pixel out of 25 pixels of 5x5 neighborhoods as shown in Fig.2. 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 equation 2 is used for grey level to binary conversion.

		P_1		
	P_2	P_3	P_4	
P_5	P_6	P_0	P_7	P_8
	P_9	P_{10}	P_{11}	
		P_{12}		

Fig.2: Third order neighborhood for a central pixel.

$$TN(P_i) = \begin{Bmatrix} 0 & \text{if} & P_i < V_0 \\ 1 & \text{if} & P_i \geq V_0 \end{Bmatrix}$$

$$\text{for } i = 1, 2, ..13 \quad (2)$$

Where V_0 is the mean of the TN-LBP and P_i is the neighboring pixel of the TN.

Step 5: The interesting thing in TN-LBP is it will have two diamond patterns. The present research named them as top diamond pattern of third order neighborhood (TDP-TN) and bottom diamond pattern of third order neighborhood (BDP-TN). Both TDP and BDP will have four pixels only. TDP-TN is indicated by green colour and BDP-TNis indicated by sky blue color in the Fig.3. The Pixels P_1, P_5, P_{12} and P_8 form TDP-TN and the pixels P_3, P_6, P_7 and P_{10}forms BDP of TN-LBP. Each of the top diamond pixels will have a distance of two from the central pixel and each of the bottom diamond pixels will form a distance of one.

		P_1		
	P_2	P_3	P_4	
P_5	P_6	P_0	P_7	P_8
	P_9	P_{10}	P_{11}	
		P_{12}		

Fig.3: Considered diamond patterns.

Step 6: Instead of evaluating the four bit LBP code on TDP-TN and BDP-TN the present paper evaluated the transitions. The four bit LBP code derives three transitions i.e. a zero, two and four transitions from 0 to 1 and 1 to 0 in a circular manner. The present paper derived frequency occurrences of uniform and non-uniform patterns on TDP and BDP of TN-LBP. The two patterns i.e 0000, 1111 forms zero transitions, and the two patterns i.e 0101, 1010 derives 4 transitions and rest of the 12 patterns derives two transitions.

Step 7: Based on the above histograms of transitions on TDP and BDP of TN of facial images an algorithm is designed to classify facial images as one of the category (child age(0-12), young age(13-30), middle age(31-50) and senior age (51 -70).

5. Results and Discussions

The proposed scheme established a database from the 1002 face images collected from FG-NET database and 500 images from Google database and other 600 images collected from scanned photographs as shown in Fig.4, 5 and 6 respectively. This leads a total of 2102 sample facial images.In the proposed method the sample images are grouped into four age groups of childage(0-12), young age(13-30), middle age(31-50) and senior age (51 -70) based on the frequency occurrences of uniform and non-uniform patterns ofTDP and BDPof TN-LBP. Table 1 and Table 2 gives the histograms of transitions on TDP and BDP of TN-LBP for child facial images on above databases respectively. In the table 0T, 2T and 4T represents the frequency occurrence of 0, 2 and 4 transitions respectively. In the similar way the remaining tables ate evaluated on young age, middle age and senior aged facial images. The age classification results of the proposed method and the existing methods are given in Table 5 and displayed in Fig.7.

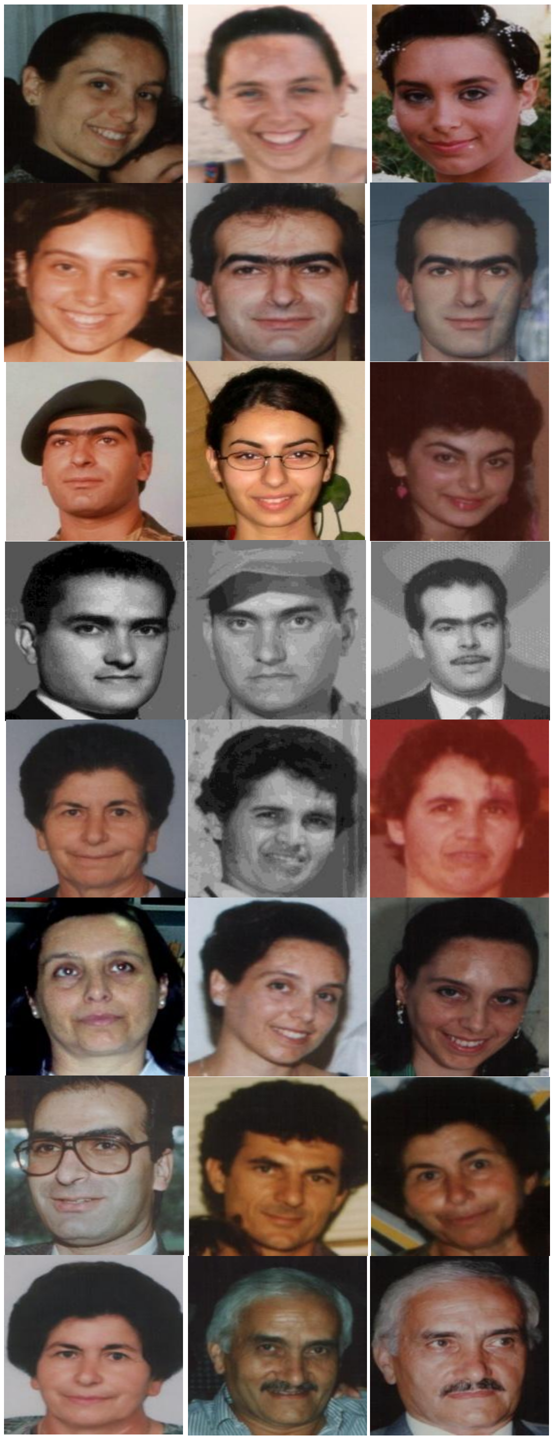

Fig.4: FGNET aging database: 011A07, 011A05, 010A07b, 001A14, 019A07, 009A14, 009A13, 009A11, 008A16, 008A13, 010A05, 010A04, 010A01, 009A09, 009A05, 004A21, 002A29, 002A26, 002A23, 002A21, 001A29, 001A28, 001A22, 009A22a, 008A21, 004A28, 004A26, 006A36, 005A40, 011A40, 001A43b, 002A31, 001A33 007A37, 005A52, 005A49, 004A53, 004A51, 048A54 , 006A61, 005A61, 004A63.

Fig.5: Google database: google_im_01, google_im_02, google_im_03, google_im_04, google_im_05, google_im_06, google_im_07, google_im_08, google_im_09, google_im_10.

Fig.6: Scanned Photographs : sca.img-001, sca.img-002, sca.img-003, sca.img-004, sca.img-005, sca.img-006.

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Table 1 (a): Histogram of transitions on facial images for child.

		Transitions on BDP of TN-LBP		
S.NO	Image_Name	0	2	4
1	001A14	501	2069	31
2	001A16	441	2013	147
3	001A19	624	1901	76
4	001A22	591	1964	46
5	001A28	492	2057	52
6	001A29	552	2014	35
7	002A15	522	2037	42
8	003A23	486	2067	48
9	011A17	595	1963	43
10	011A20	531	2032	38
11	google_im_02	448	2109	44
12	google_im_03	583	1943	75
13	google_im_04	553	1994	54
14	google_im_05	570	1989	42
15	google_im_06	540	2012	49
16	sca.img-001	640	1943	18
17	sca.img-002	540	2012	49
18	sca.img-003	570	1957	74
19	sca.img-004	491	1984	126
20	sca.img-005	603	1976	22

Table 1 (b): Histogram of transitions on facial images for child.

		Transitions on BDP of TN-LBP		
S.NO	Image_Name	0T	2T	4T
1	001A02	485	2075	41
2	001A05	443	2122	36
3	001A08	568	2003	30
4	001A10	593	1971	37
5	002A03	561	1960	80
6	002A04	643	1936	22
7	002A07	503	2038	60
8	008A06	578	1991	32
9	009A00	539	2038	24
10	010A01	538	1993	70
11	google_im_02	569	2002	30
12	google_im_03	534	2030	37
13	google_im_04	541	1986	74
14	google_im_05	525	2059	17
15	google_im_06	489	2038	74
16	sca.img-001	496	2037	68
17	sca.img-002	470	2076	55
18	sca.img-003	499	2063	39
19	sca.img-004	519	2051	31
20	sca.img-005	553	2010	38

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Table 2 (a): Histogram of transitions on facial images for young aged.

		Transitions on TDP of TN-LBP		
S.NO	Image_Name	0T	2T	4T
1	001A14	268	2229	104
2	001A16	269	2087	245
3	001A19	262	1949	390
4	001A22	266	2180	155
5	001A28	262	2234	105
6	001A29	269	2175	157
7	002A15	267	2226	108
8	003A23	259	2287	55
9	011A17	269	2194	138
10	011A20	258	2282	61
11	google_im_02	270	2280	51
12	google_im_03	265	2173	163
13	google_im_04	269	2215	117
14	google_im_05	261	2253	87
15	google_im_06	270	2271	60
16	sca.img-001	295	2165	141
17	sca.img-002	269	2214	118
18	sca.img-003	266	2192	143
19	sca.img-004	256	2174	171
20	sca.img-005	311	2147	143

Table 2(b): Histogram of transitions on facial images for young aged.

		Transitions on BDP of TN-LBP		
S.No	Image_Name	0T	2T	4T
1	001A14	501	2069	31
2	001A16	441	2013	147
3	001A19	624	1901	76
4	001A22	591	1964	46
5	001A28	492	2057	52
6	001A29	552	2014	35
7	002A15	522	2037	42
8	003A23	486	2067	48
9	011A17	595	1963	43
10	011A20	531	2032	38
11	google_im_02	448	2109	44
12	google_im_03	583	1943	75
13	google_im_04	553	1994	54
14	google_im_05	570	1989	42
15	google_im_06	540	2012	49
16	sca.img-001	640	1943	18
17	sca.img-002	540	2012	49
18	sca.img-003	570	1957	74
19	sca.img-004	491	1984	126
20	sca.img-005	603	1976	22

Algorithm 1: Age group classification based on transitions on TDP and BDP of TN-LBP.

The algorithm only considered histogram of zero and four transitions of TDP and BDP of TN-LBP respectively.

```
BEGIN

if ( 0-TDP>=270 and 4-BDP>=30 )
        print(" facial image is child");
else if ( 0-TDP<=270 and 4-BDP<=30 )
        print("facial image is senior adult");
else if ( 0-TDP>= 270 and 4-BDP<= 30 )
        print("facial image  is middle age");
else if ( 0-TDP<= 270 and 4-BDP>= 30)
        print("facial image is young ");
END
```

Table 5: Classification rate of the proposed TDP and BDP of TN-LBP method with other existing methods

Image Dataset	Existing age classification method [44]	Existing age classification method [45]	Proposed TDP and BDP of TN-LBP Method
FG-NET	89.67	90.52	90.00
Google	85.3	81.58	89.31
Scanned	88.72	85.42	91.14
Average	87.9	85.84	90.15

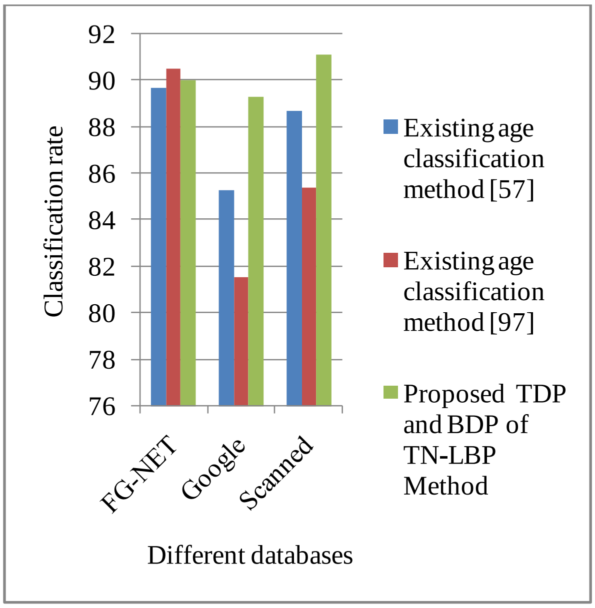

Fig.7: Comparison of classification rates in bar graph.

6. Conclusions

The present paper focussed on occurrence of uniform and non-uniform patterns on the pattern trends of TN-LBP. The frequency occurrences of uniform and non-uniform patterns on TDP and BDP of TN-LBP on all human face data sets clearly indicates 94% of the patterns are ULBP's only. The present paper is utilized the transitions on ULBP and NULBP on the proposed dual TN-LBP for an effective age classification. Based on this present research concludes that though ULBP occurs around 95 % of the patterns in the facial image, but they are not well suited for age classification. The proposed method yielded a good low classification rate when compared to the existing methods.

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