Chapter-2

TEXTON BASED SHAPE FEATURES ON LOCAL BINARY PATTERN FOR AGE CLASSIFICATION

CHAPTER 2

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S. No.	Name of Sub-Title	Page No.
2.1	Brief Outline of the Chapter	17
2.2	Introduction	18
2.3	Methodology: Age Classification Based on CGSF-ITLBP Model	19-24
2.4	Experimental Results	25-27
2.5	Comparison with other Methods	28-29
	Summary	30

CHAPTER 2

TEXTON BASED SHAPE FEATURES ON LOCAL BINARY PATTERN FOR AGE CLASSIFICATION

2.1 BRIEF OUTLINE OF THE CHAPTER

Classification and recognition of objects is interest of many researchers. Shape is a significant feature of objects and it plays a crucial role in image classification and recognition. Facial images are studied intensively in the literature for many applications like face recognition, predicting features of faces, reconstructing faces from some prescribed features, classifying gender, races and expressions from facial images, and so on. Facial aging has been an area of interest for decades [8,27,47,48,60,61], but it is only recently that efforts have been made to address problems like age estimation, age transformation, etc.

Textons are considered as texture shape primitives, which are located with certain placements rules. By considering the above advantages of LBP and textons the present thesis integrated these two methods to preserve local significant texture, edge and other primitive information to overcome the above specified disadvantages of LBP. The present thesis assumes that the features that drastically affect the adulthood classification system are the ‘Complex Geometric Shape Features’ (CGSF) of face such as various curves. The proposed Complex Geometric features represent emergent patterns showing a common property all over the image. Based on this, the present thesis proposes a new technique of adulthood classification by extracting “Complex Geometric shape features on Integrated Texton based LBP”' (CGSF-ITLBP) model images. The present thesis initially evaluates LBP features on facial images. On LBP Texton images are formed. Complex Geometric features are evaluated on ITLBP facial images for a precise age classification.

2.2 INTRODUCTION

The human face provides the observer, with much information on gender, age, health, emotion and so on. Indeed, considerable research on the human face has taken place in psychology and in the other cognitive sciences since quite early. In recent years, applications in the area of human communication were actively studied from the viewpoint of information technology. A major goal of such studies is to achieve automatic identification of individuals using computers. To incorporate a human-face database in such applications, it is required to solve the issue of age development of the human face.

While studying physical changes due to the aging process many researchers tried to classify facial images into various groups [32, 40,42,80]. The authors carried out classification of: babies and adults [69], two age groups 20-39 and 40-49 [32], sex [32,40]. LBP based age classifications are proposed in the literature. So far, no study has attempted to classify the age based on CGSF by integrating LBP and textons.

The present thesis assumes that the ability to produce accurate age-classification depends on varying trends of 'Complex Geometric Shape Features (CGSF) as age progresses. This ability has not been pursued in the computer vision community. The present chapter carried out an extensive research i.e. how the Complex Geometric Shape Features (CGSF) like circles, parabola, hyperbola, and elliptic curves vary on the proposed ITLBP model of human faces as the age progresses.

2.3 METHODOLOGY: AGE CLASSIFICATION BASED ON CGSF-ITLBP MODEL

The proposed CGSF-ITLBP model on facial images evaluates micro texture features of face and makes texture features of face relatively invariant with respect to changes in illumination, image rotation. The textons are having

- A close relationship with image features.
- Emergent patterns sharing a common property.
- Local distribution properties.

The proposed CGSF-ITLBP method of age classification consists of four steps and the block diagram is shown in Fig.2.1.

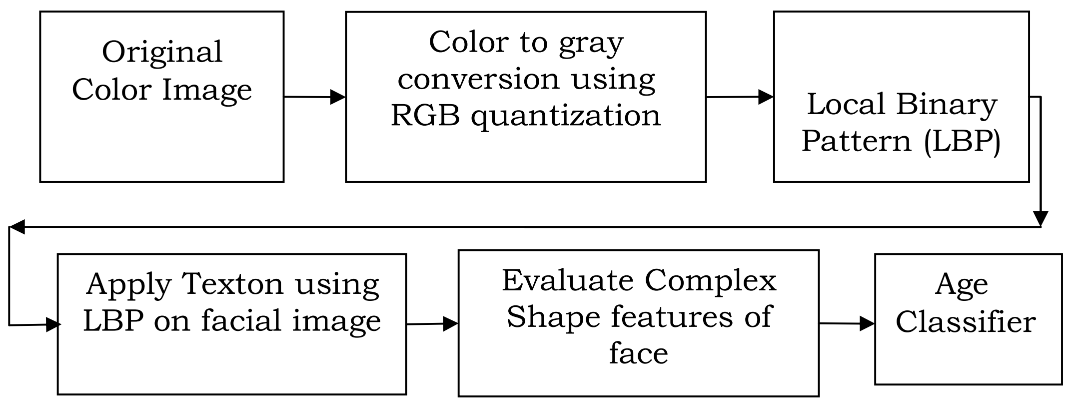


Fig.2.1: Framework for the proposed CGSF-ITLBP age classification scheme on facial images.

Step 1: Color Quantization in RGB Color Space

To convert color facial image into grey level facial image the proposed CGSF-ITLBP Model utilized RGB color quantization method.

Step 2: Local Binary Pattern

In step2 LBP is evaluated on the quantized facial image for obtaining local information in a precise way. Local Binary Pattern (LBP) is based on the concept of texture primitives[53]. This approach is a theoretically, computationally simple and efficient methodology for texture analysis. To represent the formations of a textured image, the LBP approach, models 3×3 textons as illustrated in Fig.2.2. A 3×3 circular neighborhood consists of a set of nine elements, $P = \{p_c, p_0, p_1 \ldots p_7\}$, where p_c represents the gray level value of the central pixel and p_i $(0 \leq i \leq 7)$ represent the gray level values of the peripheral pixels. Each 3×3 circular neighborhood then, can be characterized by a set of binary values b_i ($0 \le i \le 7$) as given in equation (2.1)

$$b_i = \begin{cases} 0 & \Delta p_i \ge 0 \\ 1 & \Delta p_i < 0 \end{cases} \tag{2.1}$$

where $\Delta p_i = p_i - p_c$.

For each 3×3 neighborhood, a unique LBP code is derived from the equation (2.2)

$$LBP_{P,R} = \sum_{i=0}^{i=7} b_i \times 2^i \tag{2.2}$$

Every pixel in an image generates an LBP code. A single LBP code represents local micro texture information around a pixel by a single integer code LBP ϵ [0, 255].

$$\begin{array}{|c|c|c|} \hline p_0 & p_1 & p_2 \\ \hline p_3 & p_c & p_4 \\ \hline p_5 & p_6 & p_7 \\ \hline \end{array} \longrightarrow \begin{array}{|c|c|c|} \hline b_0 & b_1 & b_2 \\ \hline b_7 & & b_3 \\ \hline b_6 & b_5 & b_4 \\ \hline \end{array} \times \begin{array}{|c|c|c|} \hline 2^0 & 2^1 & 2^2 \\ \hline 2^7 & & 2^3 \\ \hline 2^6 & 2^5 & 2^4 \\ \hline \end{array} \longrightarrow \text{LBP}$$

Fig.2.2: Representation of LBP.

The $LBP_{P,R}$ operator produces 2^P different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. Achieving rotation invariance, when the image is rotated, the gray values g_p will correspondingly move along the perimeter of the circle, so different $LBP_{P,R}$ may be computed. To achieve rotational invariance a unique identifier to each LBP is assigned in the present thesis as specified in equation (2.3).

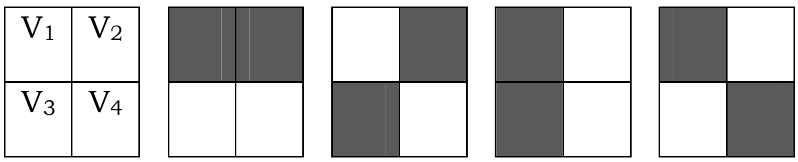
$$\mathrm{LBP}_{P,R}^{ri}(x,y) = \min\{\mathrm{ROR}(\mathrm{LBP}_{P,R}, i) \mid i = 0,1,2,\dots,P-1\} \quad (2.3)$$

where the superscript 'ri' stands for "rotation invariant". The function $\mathrm{ROR}(\mathrm{LBP}_{P,R}, i)$ performs a circular bit-wise right shift on the P-bit number $\mathrm{LBP}_{P,R}$ i times to the right ($|i| < P$).

Step 3: Texton detection on LBP image

The LBP image of step2 generates grey level image from 0 to 255 on the LBP image. The present research evaluates textons on LBP in step3. The term "texton" is conceptually proposed by Julesz [36]. Textons are effectively utilized to develop efficient models in the context of texture recognition or object recognition. Textons are image patterns that maintain a close relationship with image features and local distribution.

The present chapter utilized four texton types on a 2×2 grid as shown in Fig.2.3.



(a) (b) (c) (d) (e)

Fig.2.3: Four special types of textons: (a) 2×2 grid (b) T_1 (c) T_2 (d) T_3 and (e) T_4.

In Fig.2.3 the four pixels of a 2×2 grid are denoted as V_1, V_2, V_3 and V_4. If two pixels are highlighted in gray color of same value, the grid will form a binary 1 texton otherwise a binary 0 texton. The four texton types are denoted as T_1, T_2, T_3 and T_4 respectively as shown in Fig.2.3. The working principle of textons is illustrated in Fig.2.4.

(a)

0	3	5	0	2	2
3	1	2	1	0	3
1	0	3	4	2	1
2	5	3	2	0	3
5	0	4	3	1	0
1	5	2	4	1	5

(b)

0	3	5	0	2	2
3	1	2	1	0	3
1	0	3	4	2	1
2	5	3	2	0	3
5	0	4	3	1	0
1	5	2	4	1	5

(c)

T_2		T_1
	T_3	
T_4	T_4	T_3

(d)

1	1	0	0	1	1
1	1	0	0	1	1
0	0	1	1	0	0
0	0	1	1	0	0
1	1	1	1	1	1
1	1	1	1	1	1

(e)

Fig.2.4: Texton detection process: (a) 2×2 neighborhood sub image (b) Original facial image (c) & (d) Texton location and Texton types (e) Binary image of the face.

Step 4: Evaluation of Complex Geometric Shape Features (CGSF) on Integrated LBP Texton facial image

Shape, as a significant factor of objects, is an important research direction in image classification and recognition. As the age progresses certain shape features of face will be changing. To identify these shape features at local level, the proposed CGSF-ITLBP method captures the local information with low sensitive to changes in illumination and shape features located with certain placement rules. Based on the assumption that the local Complex Geometric features may vary as age progresses. The present thesis evaluated four complex geometric shape features i.e. $CGSF_1$, $CGSF_2$, $CGSF_3$ and $CGSF_4$ namely circle, ellipse, parabola and hyperbola respectively on ITLBP Model of facial images for a precise age classification. Frequency of occurrences of these four CGSF on ITLBP facial images are evaluated and tabulated for classification purpose.

The proposed complex set of shape features are shown in Fig.2.5 and they are represented by the equations as given from (2.4) to (2.7). All the loci of points (with the exception of the circle) are considered, using different main directions, by introducing a rotation angle of β.

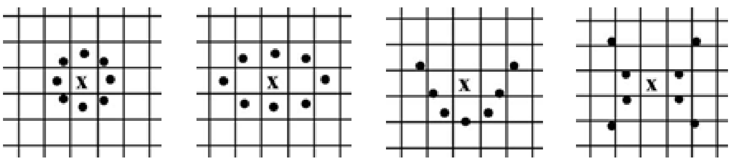
$$\text{CGSF1} = \text{circle} = x^2 + y^2 = r^2 \tag{2.4}$$

$$\text{CGSF2} = \text{Ellipse} = \frac{x^2}{a^2} + \frac{y^2}{b^2} = 1 \tag{2.5}$$

$$\text{CGSF3} = \text{Parabola} = \frac{-1}{c}x^2 + 2c = 1 \tag{2.6}$$

$$\text{CGSF4} = \text{Hyperbola} = \frac{x^2}{a^2} - \frac{y^2}{b^2} = 1 \tag{2.7}$$

where ‘r’ is the circle radius, ‘a, b’ are the semi major and semi minor axis lengths and ‘c’ is the distance between vertex and focus.



(a) (b) (c) (d)

Fig.2.5: Neighborhood topology used in this work: (a) circle (b) ellipse (c) parabola (d) hyperbola.

2.4 EXPERIMENTAL RESULTS

To show the significance of the proposed 'Complex Geometric Shape Features' (CGSF) on IT-LBP facial images the present thesis considered various facial images. The present thesis evaluated the proposed CGSF-ITLBP model on 1000 facial images considered from FG-NET aging database. Since it is not possible to show entire database, the present thesis is chosen 36 facial images as sample data base from FG-NET aging which are shown in Fig.1.4. The present study assumed that the childhood is from 0 to 18 years and from 19 years onwards as adulthood.

The frequency of occurrences of the proposed CGSF on the proposed ITLBP facial images is listed in Table 2.1 and Table 2.2 for child and adults respectively. From the Tables 2.1 & 2.2 it is clearly evident that as age progresses the frequency occurrences of CGSF on ITLBP facial images shows an increasing trend.

Table 2.1: Computed values of CGSF on ITLBP facial images for sample childhood images of FG-NET aging database.

Ages	CGSF1	CGSF2	CGSF3	CGSF4
001A04	4	3	4	0
002A04	4	3	4	0
014A03	4	2	3	5
013A08	4	3	5	0
014A03	5	3	5	0
028A05	5	0	3	5
038A04	4	2	4	3
011A07	5	2	6	0
016A07	6	3	5	1
015A07	4	1	5	1
008A08	7	0	4	3
021A10	9	4	5	4
032A10	8	4	6	0
038A11	9	5	7	3
047A12	9	6	7	1
021A11	9	6	7	4
025A12	10	7	9	3
014A12	9	5	10	3
023A14	10	6	9	2
026A13	11	8	10	4
052A14	10	6	11	5
062A12	11	7	7	3
016A16	15	11	16	6
023A16	14	8	17	0
013A16	14	9	13	4
028A17	13	9	15	7
012A18	17	10	14	5
015A17	15	6	12	5

Table 2.2: Computed values of CGSF on ITLBP facial images for sample adulthood images of FG-NET aging database.

Ages	CGSF1	CGSF2	CGSF3	CGSF4
046A20	18	12	17	6
051A22	19	13	18	7
004A21	18	11	19	6
006A22	17	10	16	7
009A23	18	12	16	4
012A24	19	9	17	0
013A24	18	12	16	4
051A24	19	13	19	0
024A25	19	10	19	5
027A25	20	15	18	7
032A28	19	14	19	8
004A28	18	11	20	5
024A28	19	10	19	6
061A29	20	12	19	7
042A28	21	9	19	6
018A29	23	8	19	10
062A30	21	13	17	9
012A30	19	6	24	12
045A32	22	10	19	0
029A33	22	13	18	6
008A41	19	10	23	3
006A42	21	12	25	5
007A42	23	11	24	9
028A46	22	14	20	6
034A44	22	6	31	6
047A43	19	10	29	0
069A46	24	15	27	6
039A50	28	12	30	10
006A51	19	14	24	6
005A52	25	8	24	8

The present thesis derived an algorithm as given in 2.1 for child and adulthood classification based on CGSF3 and CGSF1 features on IT-LBP facial images of Tables 2.1 & 2.2. The proposed algorithm gives 95% of successful child and adulthood classification. The proposed method is compared with various other existing methods and listed in Table 2.3.

Algorithm 2.1: Age classification algorithm based on CGSF on ITLBP method.

```
Begin
    if ( CGSF3  < = 14 )  then
        print "facial image as child"
    else
        if  ( (CGSF3 <=19 )  &&  (CGSF1 <= 17) ) then
        print "facial image as Child"
    else
        print "facial image as adult "
    end
End
```

2.5 COMPARISON WITH OTHER METHODS

The proposed CGSF-ITLBP Model of facial images for age classification has compared with various methods of Vijay Kumar and Chandra Mohan [9,10,11], Young H. Kwon, et al.[41], Tsuneo KANNO, et al[81]. And Wen-Bing Horng, Cheng-et al[85]. The percentage of age classification is placed in the Table.2.3.

Table 2.3: Comparison with Other Methods.

S.No	Authors	Name of the Method	% of Classification Rate	Type of Age Classification
1	Proposed Method	Texton based shape features on local binary pattern for age classification.	95%	Child and Adulthood
2	Chandra Mohan et al,[10]	Novel Method for Child and Adulthood Classification Using Linear Wavelet Transforms.	95.32	Child and Adulthood
3	Chandra Mohan et al,[9]	Age Classification of Adults Based on Topological Texture Features.	92.33	16-25, 26-35, 36-45, 46-55, 56-65, 66-75 and 76-85
4	Chandra Mohan et al,[12]	Novel Method of Adult Age Classification Using(2-level) Linear Wavelet Transforms.	93.8	16-25, 26-35, 36-45, 46-55, 56-65, 66-75 and 76-85
5	Young H. K won et al,[41]	Age Classification from Facial Images.	78	Babies, adults, and Senior adults.
6	Tsuneo KANNO et al,[81]	Classification of Age Group Based on Facial Images of Young Males by Using Neural Networks.	80	Only young males are age groups considered for classifications are 12,15,18 and 22 years

7	Wen-Bing Horng Cheng-et al,[85]	Classification of Age Groups Based on Facial Features.	90.52	Classified age groups are babies, young adults, middle-aged adults, and old adults

SUMMARY

The proposed CGSF-ITLBP model method evaluated complex shape features on a 5×5 mask using integrated texton based LBP. The proposed method has low computational complexity since it needed to evaluate only two shape parameters for a precise classification. The proposed method has low sensitivity to change in illumination. The proposed Complex Geometric Shape Features (CGSF) has shown a steady increasing trend as age progress. This phenomenon reflects that as age progress there is a steady and gradual increase of wrinkle shapes on face. Many scholars' evaluated pattern and shape based methods for age classification. The proposed CGSF-ITLBP approach is different from previous ones because, the Complex Geometric Shape Features (CGSF) are evaluated on local texture operator LBP and on emergent patterns like textons. The Table 2.3 reveals the high age classification rate of the proposed method when compared to other methods.