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An Effective Age Classification Using Topological Features Based on Compressed and Reduced Grey Level Model of the Facial Skin

Dr. V. Vijaya Kumar
Professor & Dean Computer Sciences, Anurag Group of Institutions, JNTUH, Hyderabad, A.P, India.
vijayvakula@yahoo.com

Jangala. Sasi Kiran
Research Scholar, University of Mysore, Mysore &
Associate Professor, MNR College of Engineering and Technology, Hyderabad, A.P, India.
sasikiranjangala@gmail.com

V.V. Hari Chandana
III-I Student, Dept of. Computer Science and Engineering, S.R.M.University, Chennai, India.
chandu28@gmail.com

Abstract — The present paper proposes an innovative technique that classifies human age group in to five categories i.e 0 to 12, 13 to 25, 26 to 45, 46 to 60, and above 60 based on the Topological Texture Features (TTF) of the facial skin. Most of the existing age classification problems in the literature usually derive various facial features on entire image and with large range of gray level values in order to achieve efficient and precise classification and recognition. This leads to lot of complexity in evaluating feature parameters. To address this, the present paper derives TTF's on Second Order image Compressed and Fuzzy Reduced Grey level (SICFRG) model, which reduces the image dimension from 5 x 5 into 2 x 2 and grey level range without any loss of significant feature information. The present paper assumes that bone structural changes do not occur after the person is fully grown that is the geometric relationships of primary features do not vary. That is the reason secondary features i.e TTF's are identified and exploited. In the literature few researchers worked on TTF for classification of age, but so far no research is implemented on reduced dimensionality model. The proposed Second order Image Compressed and Fuzzy Reduced Grey level (SICFRG) model reduces overall complexity in recognizing and finding histogram of the TTF on the facial skin. The experimental evidence on FG-NET aging database and Google Images clearly indicates the high classification rate of the proposed method.

Index Term — Topology; texture features; bone structure; geometrical changes; compressed model; grey value reduction

I. 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]. 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.

Other research topics include predicting feature faces [2], reconstructing faces from some prescribed features [3], classifying gender, races and expressions from facial images [4], 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 [5, 6, 7, 8, 9], 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, 11, 12, 13, 14, 15, 16, 17, 18]. Age classification problem was first worked on by Kwon and Lobo [19]. Their study classified input images as babies, young adults and senior adults based on cranio-facial development and skin wrinkle analysis. Yun et al. [20] 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. Wen-Bing Horng, Cheng-Ping Lee and Chun-Wen Chen et.al [21] considered four age groups for classification, including babies, young adults, middle-aged adults, and old adults. Their method [21] is divided into three phases: location, feature extraction, and age classification. 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 [21].

Ramanathan and Chellappa [22] 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. Ahonen et al. [23] 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. To extend this recently 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) is proposed [24].

The study of patterns on textures is recognized as an important step in characterization and recognition of texture. That is the reason the present paper investigates how the frequency occurrences of various topological texture primitive patterns or topological texture features (TTF) vary on facial image. While studying physical changes due to the aging process many researchers tried to classify facial images into various groups [25, 26, 27, 28, 29]. The authors carried out classification of: babies and adults [30], two age groups 20-39 and 40-49 [27], sex [27, 28]. Only few studies have [31] attempted to classify the age groups into five categories based on the frequency occurrences of TTF on a facial image.

So far no researcher is attempted the problem of age classification based on reducing the overall dimensionality and gray level range of the facial skin using TTF's. To address this issue and to create a new direction in the classification problem the present paper reduced a 5x5 neighborhood in to a 2x2 and also reduced the overall gray level range in to 0 to 4 and measured the frequency of occurrences of TTF's.

The present paper is organized as follows. The section 2 describes the proposed methodology and section 3 deals with the results and discussions. Conclusions are given in section 4.

II. METHODOLOGY

Local Binary Pattern (LBP), Texture Unit (TU) and Textons are useful texture descriptor that describes the characteristics of the local structure, which are useful for a significant classification. These descriptors provide a unified description including both statistical and structural characteristics of a texture. These descriptors are completely local and mostly defined on a 3 x 3 neighborhood. The proposed SICFRG model works on a 5 x 5 neighborhood, and compresses it in to a 2 x 2 neighborhood without loss of any texture information and further reduces the grey level range using fuzzy logic. The proposed method consists of ten steps. The block diagram of the proposed method is shown in Fig. 1.

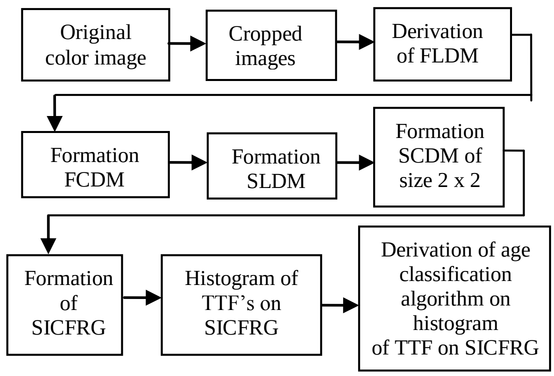

Figure 1. Block diagram for the proposed age group classification system.

A. Step - 1: The original facial image is cropped based on the two eyes location in the first step. Fig. 2 shows an example of the original facial image and the cropped image.

(a) (b)

Figure 2. a) original image b) cropped image.

B. Step - 2: RGB to HSV color model conversion: In color image processing, there are various color models in use today. In order to extract gray level features from color information, the TTF on SICFRG facial model utilized the HSV color space.

In the RGB model, images are represented by three components, one for each primary color – red, green and blue. Hue is a color attribute and represents a dominant color. Saturation is an expression of the relative purity or the degree to which a pure color is diluted by white light. HSV color space is a non-linear transform from RGB color space that can describe perceptual color relationship more accurately than RGB color space. HSV color space is formed by hue (H), saturation (S) and value (V). Hue denotes the property of color such as blue, green, red. Saturation denotes the perceived intensity of a specific color. Value denotes brightness perception of a specific color. However, HSV color space separates the color into hue, saturation, and value which means observation of color variation can be individually discriminated. In order to transform RGB color space to HSV color space, the transformation is described as follows:

The transformation equations for RGB to HSV color model conversion is given below.

$$V = \max(R, G, B) \tag{1}$$

$$S = \frac{\mathrm{V-min(R,G,B)}}{\mathrm{V}} \tag{2}$$

$$\mathrm{H} = \frac{\mathrm{G-B}}{6\mathrm{S}} \quad if \quad \mathrm{V = R} \tag{3}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{B-R}}{6\mathrm{S}} \quad if \quad \mathrm{V = G} \tag{4}$$

$$\mathrm{H} = \frac{1}{3} + \frac{\mathrm{R-G}}{6\mathrm{S}} \quad if \quad \mathrm{V = B} \tag{5}$$

where the range of color component Hue (H) is [0,255], the component saturation (S) range is [0,1] and the Value (V) range is [0,255]. In this work, the color component Hue (H) is considered as color information for the classification of facial images. Color is an important attribute for image processing applications.

C. Step - 3: Formation of nine overlapped sub 3 x 3 neighborhoods from a 5 x 5 neighborhood: A neighborhood of 5x5 pixels is denoted by a set containing 25 pixel elements P= {P_{11},…., P_{33}, ...P_{55}}, here P_{33} represents the intensity value of the central pixel and remaining values are the intensities of neighboring pixels as shown in Fig. 3.

Fig. 4 represents the formation of nine overlapped 3 x 3 sub neighborhoods represented as {n1, n2, n3, n9} from the Fig. 3.

P_{11}	P_{12}	P_{13}	P_{14}	P_{15}
P_{21}	P_{22}	P_{23}	P_{24}	P_{25}
P_{31}	P_{32}	P_{33}	P_{34}	P_{35}
P_{41}	P_{42}	P_{43}	P_{44}	P_{45}
P_{51}	P_{52}	P_{53}	P_{54}	P_{55}

Figure 3. Representation of a 5 x 5 neighborhood.

P_{11}	P_{12}	P_{13}
P_{21}	P_{22}	P_{23}
P_{31}	P_{32}	P_{33}

n1

P_{12}	P_{13}	P_{14}
P_{22}	P_{23}	P_{24}
P_{32}	P_{33}	P_{34}

n2

P_{13}	P_{14}	P_{15}
P_{23}	P_{24}	P_{25}
P_{33}	P_{34}	P_{35}

n3

P_{21}	P_{22}	P_{23}
P_{31}	P_{32}	P_{33}
P_{41}	P_{42}	P_{43}

n4

P_{22}	P_{23}	P_{24}
P_{32}	P_{33}	P_{34}
P_{42}	P_{43}	P_{44}

n5

P_{23}	P_{24}	P_{25}
P_{33}	P_{34}	P_{35}
P_{43}	P_{44}	P_{45}

n6

P_{31}	P_{32}	P_{33}
P_{41}	P_{42}	P_{43}
P_{51}	P_{52}	P_{53}

n7

P_{32}	P_{33}	P_{34}
P_{42}	P_{43}	P_{44}
P_{52}	P_{53}	P_{54}

n8

P_{33}	P_{34}	P_{35}
P_{43}	P_{44}	P_{45}
P_{53}	P_{54}	P_{55}

n9

Figure 4. Formation of nine overlapped 3 x 3 neighborhoods {n1, n2, n3, …,, n9} from figure. 3.

D. Step - 4: Derivation of First order Local Difference Matrix (FLDM) on the overlapped neighborhoods of 3 x 3 of step three: The FLDM gives an efficient representation of face images. The FLDM is obtained by the absolute difference between the neighboring pixel and the gray value of the central pixel from each of the 3 x 3 neighborhoods i.e. n1 to n9 of step 3. The FLDM mechanism is described by the (6) and shown in Fig. 5. This forms nine new 3 x 3 FLDM's and represented as { $FLDM_1$, $FLDM_2$, $FLDM_3$,…….., $FLDM_9$}.

$$FLDM_i = abs\ (P_i - P_c) \text{ for } i = 1,2,...9 \tag{6}$$

where p_c and p_i are the central pixel and neighboring pixel values of the overlapped 3 x 3 neighborhood {n1,n2,…n9).

The (6) demonstrates that always central pixel value of the 3 x 3 FLDM is zero.

$\lvert P_{11}-P_{22}\rvert$	$\lvert P_{12}-P_{22}\rvert$	$\lvert P_{13}-P_{22}\rvert$
$\lvert P_{21}-P_{22}\rvert$	$\lvert P_{22}-P_{22}\rvert$	$\lvert P_{23}-P_{22}\rvert$
$\lvert P_{31}-P_{22}\rvert$	$\lvert P_{32}-P_{22}\rvert$	$\lvert P_{33}-P_{22}\rvert$

Figure 5. formation of $FLDM_1$ from n1.

E. Step - 5: Formation of First order Compressed Difference Matrix (FCDM) of size 3 x 3 from 5 x 5: In step five each pixel value of FCDM is evaluated from each of the nine FLDM's of step 2 as given in (7). The FCDM is a 3 x 3 matrix with nine pixel elements ($FCDP_1$ to $FCDP_9$). The FCDM maintains the local neighborhood properties including edge information.

$$FCDP_i = Avg \text{ of } (FLDM_i) \text{ for } i = 1,2,…9 \tag{7}$$

F. Step- 6: Formation of Second order Local Difference Matrix (SLDM): In step six SLDM is obtained on the FCDM of step 5 using the (8). The SLDM is shown in Fig. 6a.

$$SLDP_i = abs\ (FCDP_i – FCDP_c) \text{ for } FCDP_i = 1,2,…9 \tag{8}$$

where $FCDP_c$ and $FCDP_i$ are the central pixel and neighboring pixel values of the FCDM.

The SLDM matrix is shown in Fig. 6a. The (8) demonstrates that always central pixel value of the 3 x 3 SLDM is zero

$SLDP_1$	$SLDP_2$	$SLDP_3$
$SLDP_4$	$SLDP_5$	$SLDP_6$
$SLDP_7$	$SLDP_8$	$SLDP_9$

(a)

TSP_1	TSP_2
TSP_3	TSP_4

(b)

Figure 6. Generation process of a SCDM of size 2×2 from a 3 x 3 SLDM neighborhood.
a) The SLDM neighborhood b) SCDM.

G. Step - 7: Formation of Second order Compressed Difference Matrix (SCDM) of size 2 x 2 from step six: In step 7 the SLDM of a 3×3 neighbourhood is reduced into a 2×2 SCDM by using Triangular Shape Primitives (TSP). The proposed TSP is a connected neighbourhood of three pixels on a 3 x 3 SLDM, without central pixel. The TSP's on SLDM is not considered central pixel because its gray level value is always zero. The average of these TSP's generates pixel values of Second order Compressed Difference Matrix (SCDM) of size 2×2 as shown in Fig. 6 and as represented in (9), (10), (11), and (12). By this the proposed method reduces the original image of size N×M into the size (2N/5) ×(2M/5).

$$TSP_1 = \frac{SLDP_1+SLDP_2+SLDP_4}{3} \quad (13)$$

$$TSP_2 = \frac{SLDP_2+SLDP_3+SLDP_6}{3} \quad (14)$$

$$TSP_3 = \frac{SLDP_4+SLDP_7+SLDP_8}{3} \quad (15)$$

$$TSP_4 = \frac{SLDP_6+SLDP_8+SLDP_9}{3} \quad (16)$$

H. Step - 8: Reduction of grey level range on SCDM using fuzzy logic: Fuzzy logic has certain major advantages over traditional Boolean logic when it comes to real world applications such as texture representation of real images. To deal accurately with the regions of natural images even in the presence of noise and the different processes of caption and digitization fuzzy logic is introduced on SCDM. The proposed fuzzy logic converts the SCDM grey level range in to 5 levels ranging from 0 to 4. That is the reason the derived model is named as SICFRG model**.** In LBP binary patterns are evaluated by comparing the neighboring pixels with central pixel. The proposed Second order Image Compressed and Fuzzy Reduced Grey level (SICFRG) model is derived by comparing the each pixel of the 2×2 SCDM with the average pixel values of the SCDM. The SICFRG representation is shown in Fig. 7. The following (13) is used to determine the elements of SICFRG model.

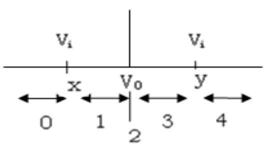

Figure 7. Fuzzy representation of SCDM model of the image

$$SICFRG_i = \begin{cases} 0 \text{ if } TSP_i < V_0 \text{ and } TSP_i < x \\ 1 \text{ if } TSP_i < V_0 \text{ and } TSP_i \geq x \\ 2 \text{ if } TSP_i = V_0 \\ 3 \text{ if } TSP_i > V_0 \text{ and } TSP_i > y \\ 4 \text{ if } TSP_i > V_0 \text{ and } TSP_i \leq y \end{cases}$$

for i = 1, 2, 3, 4 (13)

where x, y are the user-specified values.

$$where\ V_0 = \frac{(\sum_{i=1}^{4} TSP_i)}{4} \quad (14)$$

For example, the process of evaluating SICFRG model from a sub SCDM image of 2×2 is shown in Fig. 8. In this example x and y are chosen as $\frac{V_0}{2}$ and $\frac{3V_0}{2}$ respectively.

28	39
60	9

(a)

1	2
4	0

(b)

Figure 8. The process of evaluating SICFRG model from SCDM
(a) SCDM (b) SICFRG model.

I. Step - 9: Find the occurrences of Bezier curves (12 patterns) with different control points, U, V and T patterns on each of the different fuzzy grey levels 0, 1, 2, 3 and 4 as described in section 2.1.

J. Step - 10: Based on the frequency occurrences of above TTF of SICFRG model on the facial image, the image is classified as child (0-12), young adults (13-25), middle adults (26-45), senior adults (46-60), and old adults (above 60).

2.1 Evaluation of the frequency occurrences of TTF on SICFRG facial Images:

The present Paper initially converts facial image in to SICFRG model, which reduces the overall dimension into (2N/5 x 2M/5) with grey levels ranging from 0 to 4 and while preserving the important texture features and edge information without any loss.

The proposed TTF on SICFRG is considered an exhaustive number of Bezier curves because they represent good topological changes of facial skin as age progress out. The present research considered Bezier curves with twelve different control points on each 5 x 5 mask as shown in Fig. 9. The TTF i.e. U, V and T patterns on a 5x5 mask are shown in Fig. 10.

TTF are evaluated on each of the fuzzy values. That is the frequency occurrences of Bezier curves with different fuzzy grey level values i.e. 0, 1, 2, 3 and 4 are evaluated and denoted as B0, B1, B2, B3 and B4 respectively. In the same way U, V, T patterns are evaluated with different fuzzy grey level values. To have a precise and accurate age group classification, the present study considered sum of the frequencies of occurrences of all TTF's.

1	1	0	0	0
0	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	0	1
CP (1, 2), (2,1)				

1	1	0	0	0
0	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (1,3), (3,1)				

1	1	0	0	0
0	1	1	0	0
0	0	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (1,4), (4,1)				

1	1	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	0	0
0	0	1	1	1
CP (1,5), (5,1)				

1	0	0	0	0
1	1	1	0	0
0	0	1	0	0
0	0	1	1	0
0	0	0	1	1
CP (2,1), (1,2)				

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1
CP (1,1), (1,1)				

1	0	0	0	0
1	1	1	0	0
0	0	1	1	0
0	0	0	1	1
0	0	0	0	1
CP (3,1), (1,3)				

1	0	0	0	0
1	1	0	0	0
0	1	1	1	0
0	0	0	1	1
0	0	0	0	1
CP (3,2), (2,3)				

1	1	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	0
0	0	0	1	1
CP (3,5), (5,3)				

1	0	0	0	0
0	1	1	0	0
0	0	1	1	0
0	0	0	1	0
0	0	0	1	1
CP (4,5), (5,4)				

1	0	0	0	0
1	0	0	0	0
1	1	1	1	1
0	0	0	0	1
0	0	0	0	1
CP (5,1), (1,5)				

1	0	0	0	0
1	1	0	0	0
0	1	1	0	0
0	0	1	1	1
0	0	0	0	1
CP (5,3), (3,5)				

Figure 9. Bezier curve patterns on a 5×5 window with 0^0 orientation using various control points (CP) with fuzzy value 1.

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

(a)

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

(b)

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

(c)

Figure 10. Alphabetic patterns on a 5×5 mask with 0^0 orientations with fuzzy value 1.
(a)U-pattern, (b) V-pattern, (c) T-pattern.

III. RESULTS AND DISCUSSIONS

The present paper established a database from the 1002 face images collected from FG-NET database and other 600 images collected from the scanned photographs. This leads a total of 1602 sample facial images. In the proposed TTF on SICFRG model the sample images are grouped into five age groups of 0 to 12, 13 to 25, 26 to 45, 46 to 60, and above 60 based on the frequency of occurrence of TTF's of the facial image. The table one clearly indicates the frequency occurrences of Bezier curves with different control points with different grey level values. In the table 1 Bo, Uo, Vo and To represents the sum of frequency occurrences or histograms of Bezier curves, U, V, T patterns respectively with fuzzy grey level value0.

From the table 1 it is observed that fuzzy grey level value 2 on the SICFRG model has formed majority of TTF and remaining fuzzy grey level values does not form any TTF. So, for classification purpose the present research evaluated and considered only fuzzy grey level value 2.

The table 2 clearly represents Frequency occurrences of TTF on SICFRG model with grey level value 2. In table 2 STTF indicates the sum of frequencies of all TTF with fuzzy grey level value 2.

Based on the STTF on SICFRG model with fuzzy grey level 2 on FG-NET ageing database an algorithm is derived for an efficient age classification into five groups which is shown in algorithm 1. The Fig. 11 indicates the classification graph.

Algorithm 1: Age group classification based on sum of frequency occurrences of TTF (STTF) on SICFRG model with grey level value 2 on FG-NET ageing database.

BEGIN
Let the sum of frequencies of TTF is denoted as STTF.
if (STTF < 650)
Print (facial image age is old adults (> 60))
Else if (STTF < 950)
    Print (facial image age is senior adults (46-60))
Else if (STTF < 1100)
    Print (facial image age is middle-aged adults (26-45))
Else if (STTF < 1350)
    Print (facial image age is young adults (13-25))
Else
    Print (facial image age is child (0-12))
End

TABLE 1: Frequency occurrences of TTF using SICFRG on FG-NET sample ageing database

S. No.	Image Name	B0	B1	B2	B3	B4	U0	U1	U2	U3	U4	V0	V1	V2	V3	V4	T0	T1	T2	T3	T4
1	001A05	0	0	1258	0	0	0	0	65	0	0	0	0	111	0	0	0	0	114	0	0
2	001A08	0	0	1155	0	0	0	0	61	0	0	0	0	99	0	0	0	0	95	0	0
3	008A12	0	0	1110	0	0	0	0	69	0	0	0	0	109	0	0	0	0	116	0	0
4	001A14	0	0	1041	0	0	0	0	69	0	0	0	0	84	0	0	0	0	110	0	0
5	001A18	0	0	937	0	0	0	0	38	0	0	0	0	74	0	0	0	0	84	0	0
6	001A22	0	0	1052	0	0	0	0	58	0	0	0	0	90	0	0	0	0	85	0	0
7	001A28	0	0	841	0	0	0	0	47	0	0	0	0	64	0	0	0	0	77	0	0
8	001A33	0	0	779	0	0	0	0	51	0	0	0	0	68	0	0	0	0	76	0	0
9	001A40	0	0	860	0	0	0	0	31	0	0	0	0	66	0	0	0	0	65	0	0
10	003A47	0	0	656	0	0	0	0	32	0	0	0	0	55	0	0	0	0	52	0	0
11	006A55	0	0	753	0	0	0	0	52	0	0	0	0	63	0	0	0	0	68	0	0
12	003A60	0	0	614	0	0	0	0	41	0	0	0	0	59	0	0	0	0	73	0	0
13	006A61	0	0	491	0	0	0	0	28	0	0	0	0	52	0	0	0	0	54	0	0
14	004A63	0	0	361	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0
15	006A69	0	0	379	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0

TABLE 2: Frequency occurrences of TTF on SICFRG model with grey level value 2 on FG-NET ageing database.

S. No.	Image Name	B2	U2	V2	T2	STTF
1	001A05	1258	65	111	114	1548
2	001A08	1155	61	99	95	1410
3	008A12	1110	69	109	116	1404
4	008A03	1135	62	107	113	1417
5	001A02	1127	62	107	98	1394
6	002A12	1207	67	98	111	1483
7	002A07	1234	63	112	106	1515
8	002A05	1198	64	106	103	1471
9	008A06	1164	69	103	104	1440
10	001A10	1153	71	101	99	1424
11	001A14	1041	69	84	110	1304
12	001A18	937	38	74	84	1133
13	001A22	1052	58	90	85	1285
14	008A13	938	48	84	85	1155
15	002A16	1034	45	67	113	1259
16	002A23	937	43	91	87	1158
17	001A19	1064	57	85	93	1299
18	002A15	1103	47	81	89	1320
19	002A16	1106	54	75	91	1326
20	002A20	1057	49	81	90	1277
21	001A28	841	47	64	77	1029
22	001A33	779	51	68	76	974
23	001A40	860	31	66	65	1022
24	005A45	878	33	65	79	1055
25	002A26	913	32	66	77	1088
26	002A31	918	39	64	68	1089
27	002A29	897	37	67	72	1073
28	002A36	895	36	67	69	1067
29	002A38	799	41	69	73	982
30	003A35	817	37	65	71	990
31	003A47	656	32	55	52	795
32	006A55	753	52	63	68	936
33	003A60	614	41	59	73	787
34	004A48	714	43	61	67	885
35	004A53	721	45	57	63	886
36	006A59	672	39	54	71	836
37	003A49	715	46	49	70	880
38	003A51	694	50	61	73	878
39	003A58	599	46	56	71	772
40	004A51	619	43	54	68	784
41	006A61	491	28	52	54	625
42	004A63	361	14	29	35	439
43	006A69	379	15	35	36	465
44	004A66	619	27	36	43	725
45	006A67	437	19	48	52	556
46	006A69	515	23	43	39	620
47	004A62	493	18	45	37	593
48	005A61	415	19	38	43	515
49	005A63	468	24	41	44	577
50	004A65	375	28	42	42	487

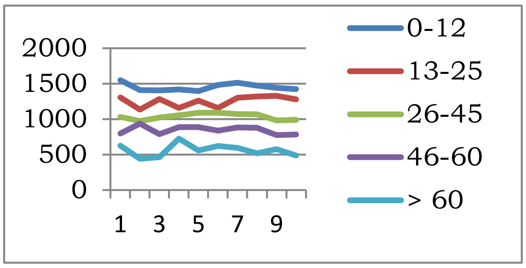

Figure 11. Age Classification graph based on the proposed method.

To evaluate the accuracy, and significance of the proposed TTF on SICFRG model probe or test images are taken. On probe image, STTF's with fuzzy grey level value 2 is evaluated on the facial image. As an experimental case 40 face samples, randomly collected from FG-NET, Google database and some Scanned images, are tested with the proposed method and the results are given in Table 3. The classification percentage of three datasets is shown in table 4 and classification graph of three datasets are shown in Fig. 12.

TABLE 3: Classification results of the proposed TTF on SICFRG model on test images.

S. No	Image Name	B2	U2	V2	T2	STTF	Classified Age Group	Results
1	001A0	1227	6	1	1	1519	0-12	Succes
2	002A1	1025	5	8	8	1256	13-25	Succes
3	003A2	976	4	7	8	1183	13-25	Succes
4	005A2	1075	4	8	9	1296	13-25	Succes
5	063A0	1137	6	9	1	1406	0-12	Succes
6	064A1	1024	5	8	1	1259	13-25	Succes
7	064A5	707	3	5	6	869	46-60	Succes
8	065A0	1107	6	1	9	1380	0-12	Succes
9	067A1	1036	5	7	9	1267	13-25	Succes
10	022A2	854	3	6	7	1029	26-45	Succes
11	023A2	789	5	5	7	970	26-45	Succes
12	024A3	878	4	5	8	1063	26-45	Succes
13	025A4	697	3	5	7	865	46-60	Succes
14	027A3	889	3	5	7	1055	26-45	Succes
15	017A6	462	1	3	3	558	>60	Succes
16	018A3	819	3	6	6	986	26-45	Succes
17	020A3	835	3	6	6	1000	26-45	Succes
18	025A5	434	2	4	3	532	>60	Succes
19	Sci-1	905	4	6	6	1079	26-45	Succes
20	Sci-2	837	4	6	7	1012	26-45	Succes
21	Sci-3	993	4	7	8	1205	13-25	Succes
22	Sci-4	796	3	6	6	954	26-45	Succes
23	Sci-5	814	4	5	6	978	26-45	Succes
24	Sci-6	1023	4	8	8	1232	13-25	Succes
25	Sci-7	1102	4	8	8	1308	13-25	Succes
26	Sci-8	1075	4	7	9	1298	13-25	Succes
27	20-2	1057	5	8	9	1284	13-25	Succes
28	25-1	827	3	6	6	998	26-45	Succes
29	25-2	819	3	6	7	990	26-45	Succes
30	25-3	847	3	5	7	1009	26-45	Succes
31	40-6	857	3	5	6	1014	26-45	Succes
32	40-1	836	2	5	6	985	26-45	Succes
33	40-2	704	3	6	7	877	46-60	Succes
34	40-3	697	4	6	7	879	46-60	Succes
35	40-4	667	4	6	6	842	46-60	Succes
36	40-5	513	1	3	4	609	>60	Succes
37	35-1	473	2	3	4	576	>60	Succes
38	50-1	635	4	6	6	808	46-60	Fail
39	50-2	514	2	4	4	627	>60	Succes
40	50-3	399	2	4	4	505	>60	Succes

TABLE 4: Classification results of three datasets on proposed TTF on SICFRG model.

Image Dataset	FG-NET database	Google database	Scanned images
Child	100.00%	97.50%	97.50%
Young adults	100.00%	97.50%	95.00%
Middle Adults	100.00%	95.00%	95.00%
Senior Adults	97.50%	95.00%	97.50%
Old Adults	100.00%	97.50%	97.50%

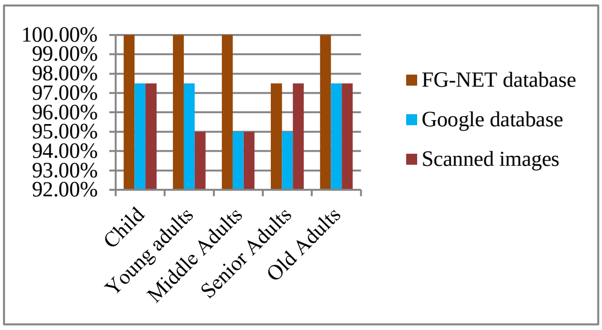

Figure 12. Mean classification of three datasets.

IV. COMPARISON WITH OTHER EXISTING METHODS:

The proposed TTF on SICFRG model is compared with Morphological Primitive Patterns with Grain Components on LDP approach [24] and geometric properties [29] methods. The percentage of classification rates of the proposed TTF on SICFRG model and other existing methods [24, 31] are listed in table 5. The table 5 clearly indicates that the proposed method yields better classification rate when compared with existing methods. Fig. 13 shows the comparison chart of the proposed TTF on SICFRG model with the other existing methods of table 5.

TABLE 5: % mean classification rates for proposed TTF-SICFRG method and other existing methods.

Image Dataset	Morphological Primitive Patterns with Grain Components on	Geometric properties	proposed TTF on SICFRG model
Child	92.17%	91.04%	97.50%
Young adults	93.37%	92.71%	95.00%
Middle Adults	92.56%	90.07%	97.50%
Senior Adults	92.40%	92.10%	95.00%
Old Adults	91.90%	91.60%	97.50%

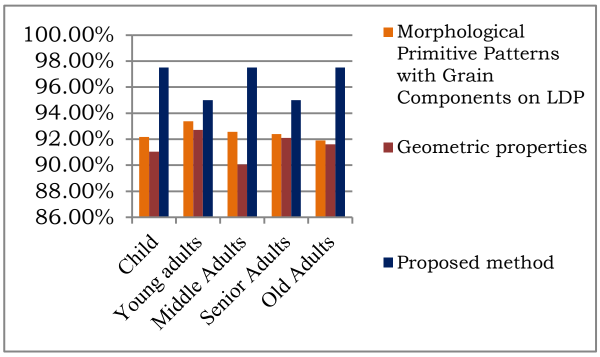

Figure 13. Comparison graph of proposed TTF on SICFRG model with other existing methods.

V. SUMMARY

The present paper developed a new direction for age group classification using frequency occurrences of TTF on SICFRG. The proposed method reduces overall dimensionality drastically while preserving the texture edge and other significant features. The proposed method reduces the overall complexity of classification algorithm because of the facial image size is reduced from N×M to 2N/5 ×2M/5 and also reduced the gray level range 0 to 4. The TTF's are evaluated on each of the fuzzy gray level and found that only TTF's are formed only on fuzzy gray level value 2. The other important feature of the present TTF on SICFRG is out of these TTF Bezier curve estimates, the rapid topological changes in the skin at a higher rate, which is the reason an exhaustive number of Bezier curves with twelve different control points are estimated on each 5 x 5 mask. The performance of the present system is more effective for the FG-NET aging database when compare with Google Images and scanned images.

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REFERENCES

[1] Chellappa, R., Wilson, C.L. and Sirohey, S., " Human and machine recognition of faces: A survey, " proc. of the IEEE, vol.83, pp. 705-740 (1995).
[2] Choi, C., "Age change for predicting future faces", proc. IEEE Int. Conf. on fuzzy systems, vol 3, pp. 1603-1608 (1999).
[3] A. Lanitis, C. Draganova, and C. Christodoulou. Comparing different classifiers for automatic age estimation. IEEE Transactions on Systems, Man, and Cybernetics, Part B, 34(l):621-628, February 2004.
[4] Y. H. Kwon and N. V. Lobo,"Age classification from facial images," Computer Vision and Image Understanding, vol.74, no.1 pp.1-21, 1999.
[5] B. Pittenger and R. E. Shaw. Aging faces as viscal-elastic events: Implications for a theory of nonrigid shape perception. Journal of Experimental Psychology: Human Perception and Performance, 1(4):374-382 1975.
[6] J. B. Pittenger, R. E. Shaw, and L. S. Mark. Perceptual information for the age level of faces as a higher order invariant of growth. Jourtal of Experimental Psychology: Hufman Perception and Per-finance, 5(3):478-493, 1979.
[7] L. S. Mark and J. T. Todd. The perception of growth in three dimensions. Jourrial ofPerception and Psychophysics, 33(2):193-196, 1983.
[8] L. S. Mark, J. B. Pittenger, H. Hines, C. Carello, R. E. Shaw, and J. T. Todd. "Wrinkling and head shape as coordinated sources of age level information", Journal of Perception and Psychophysics, 27(2):1L17-124, 1980.
[9] D. Burt and D. Perrett. Perception of age in adult caucasian male faces: computer graphic manipulation of shape and colour information. Proceedings of the Royal Society ofLondon B, B-259:137-143, 1995.
[10] Kwon, Y. H. and da Vitoria Lobo, N., "Age classification from facial images," Proc. IEEE Conf. on Computer Vision and Pattern Recognition, Seattle, Washington, U. S. A., pp. 762-767 (1994).
[11] Y Wu, N. Thalmaun, and D. Thalimnann. A dynaimnic wrinkle model in facial animation and skin aging. Journal of Visualization and Computer Animation, 6:195-205, 1995.
[12] A. Lanitis, C. Draganova, and C. Christodoulou. Comparing different classifiers for automatic age estimation. IEEE Transactions on Systems, Man, and Cybernetics, Part B, 34(l):621-628, February 2004.
[13] A. Lanitis, C. Taylor, and T. Cootes. Toward automatic simulation of aging effects on face images. IEEE Tran.sactions on Pattern Analysis and Machine Intelligence, 24(4):442-455, April 2002.
[14] N. Ramanathan and R. Chellappa. Face verification across age progression. IEEE Transactions on lmage Processing, 15(11L):3349-3361, November 2006.
[15] C. Scandrett, C. Solomon, and S. Gibson. A personspecific, rigorous aging model of the human face. Prttern Recogtnioti Letters, 27(15):1776-1787B November 2006.
[16] J. Suo, F. Min, S. Zhu, S. Shan, and X. Chen. A multiresolution dynamic model for face aging simulation. In IEEE Conference of Computer Vision and Pattern Recognition, pages 1-8B 2007.
[17] X. Geng, Z. Zhou, and K. Smith-Miles. Automatic age estimation based on facial aging patterns. IEEE Transactions on Pattern Analysis and Machine Ititelligence, 29(12):2234-2240, December 2007.
[18] N. Ramanathan and R. Chellappa. Modeling age progression in young faces. In Proceedings of IEEE International Con/conference on Computer Vision and Porttern Recognition, pages 387-394, 2006.
[19] Kwon, Y. H. and da Vitoria Lobo, N., "Age classification from facial images," Proc. IEEE Conf. on Computer Vision and Pattern Recognition, Seattle, Washington, U. S. A., pp. 762-767 (1994).
[20] F. Yun, X. Ye and T. S. Huang, "Estimating Human Age by Manifold Analysis of Face Pictures and Regression on Aging Features," in Proc. of 2007 IEEE International Conference on Multimedia and Expo, 2007, pp. 1383-1386.
[21] Wen-Bing Horng, Cheng-Ping Lee and Chun-Wen Chen "Classification of Age Groups Based on Facial Features", Tamkang Journal of Science and Engineering, Vol. 4, No. 3, pp. 183-192 (2001).
[22] N. Ramanathan and R. Chellappa. Face verification across age progression. In IEEE Conference on Computer Vision and Pattern Recognition, volume 2, pages 462–469, San Diego, U.S.A, 2005.
[23] T. Ahonen, A. Hadid, M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition", IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 12, pp. 2037 –2041, 2006.
[24] B.Sujatha, Dr.V.Vijaya Kumar, M.Rama Bai "Morphological Primitive Patterns with Grain Components on LDP for Child and Adult Age Classification" in International Journal of Computer Applications (0975 – 8887) Volume 21– No.3, pp. 50-55, May 2011.
[25] Todd J. T., Mark L. S., Shaw R. E. and Pittenger J. B. "The perception of human growth," Scientific American, 242(2):132–144, 1980.
[26] Kwon Y. H. and da Vitoria Lobo N. "Age classification from facial images," Proc. IEEE Conf. on Computer Visionand Pattern

Recognition, Seattle, Washington, U. S. A., pp. 762-767 (1994).

[27] Hasegawa H. and Simizu E. “Discrimination of facial age generation using neural networks,” T.IEE Japan, vol.117-C, no.12, pp.1897–1898, 1997.

[28] Kosugi M. “Human-face recognition using mosaic pattern and neural networks,” IEICE Trans., vol.J76-D-II, no.6, pp.1132–1139, June 1993.

[29] Chandra Mohan M., Vijaya Kumar V. and Damodaram A. ”Novel Method of Adulthood Classification based on Geometrical Features of Face,” Accepted by GVIP Journal of Graphics, Vision and Image Processing, to publish in June, 2010 issue.

[30] Sirovich L. and Kirby M. “Low-dimensional procedure for the characterization of human face,” J. Opt. Am. A, vol.7, no.3, pp.519–524, 1987.

[31] Chandra Mohan M., Vijaya Kumar V. and Venkata Krishna V. ”Novel Method of Adult Age Classification Using Linear Wavelet Transforms,” IJCSNS International Journal of Computer Science and Network Security, VOL. 10 No. 3, pp. 61-68, March, 2010.

AUTHORS PROFILE

Vakulabharanam Vijaya Kumar received integrated M.S. Engg, degree from Tashkent Polytechnic Institute (USSR) in 1989. He received his Ph.D. degree in Computer Science from Jawaharlal Nehru Technological University (JNTU) in 1998. He has served the JNT University for 13 years as Assistant Professor and Associate Professor and taught courses for M.Tech students. He has been Dean for Dept of CSE and IT at Godavari Institute of Engineering and Technology since April, 2007. His research interests include Image Processing, Pattern Recognition, Network Security, Steganography, Digital Watermarking, and Image retrieval. He is a life member for CSI, ISTE, IE, IRS, ACS, ISC, NRSA and CS. He has published more than 150 research publications in various National, Inter National conferences, proceedings and Journals. He has received best researcher, best teacher awards from JNTUK Kakinada and Gold plated silver award from Indian Red Cross Society.

J. Sasi Kiran Graduated in B.Tech. from JNTU University in 2002. He received Masters Degree in M.Tech. from Bharath University, Chennai, in 2005 and pursuing Ph.D from University of Mysore, Mysore in Computer Science under the guidance of Dr V. Vijaya Kumar. He served as an Associate Professor in Vidya Vikas Institute of Technology, Hyderabad from 2004 to 2013 and working as Associate Professor in CSE Dept. in MNR College of Engg. & Tech, Sangareddy, Medak Dt, A.P, India. His research interests include Network Security, Digital Watermarking, and Pattern Recognition & Image Analysis. He has published research papers in various National, International conferences, proceedings and Journals. He is a life member of ISTE, ISC and management committee member of CSI. He has received significant contribution award from CSI India.

Chandana Vinayaka .V is pursuing her Engineering in CSE at SRM University, Chennai and presently in 3rd year. She has participated in various Student symposiums and Seminars. Her research areas include Image Processing, Cyber Laws and Digital Watermarking.

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