AGE CLASSIFICATIONS BASED ON SECOND ORDER IMAGE COMPRESSED AND FUZZY REDUCED GREY LEVEL (SICFRG) MODEL

Jangala. Sasi Kiran
Research Scholar, University of Mysore, Mysore.
Associate Professor & HOD-CSE
Vidya Vikas Institute of Technology, Hyderabad, A.P, India.
E-mail: jsasikiranj@yahoo.co.in

Dr. V. Vijaya Kumar
Professor & Dean Computer Sciences,
Anurag Group of Institutions, Hyderabad, A.P, India.
E-mail: vakulabharanam@hotmail.com

Dr. B. Eswara Reddy
Professor, CSE Dept, JNTUA College of Engineering, Anantapur, A.P, INDIA.
E-mail: eswarcsejntu@gmail.com

ABSTRACT

One of the most fundamental issues in image classification and recognition are how to characterize images using derived features. Many texture classification and recognition problems in the literature usually require the computation on entire image set 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 a Second Order image Compressed and Fuzzy Reduced Grey level (SICFRG) model, which reduces the image dimension and grey level range without any loss of significant feature information. The present paper derives GLCM features on the proposed SICFRG model for efficient age classification that classifies facial image into a five groups. The SICFRG image mode of age classification is derived in three stages. In the first stage the 5 x 5 matrix is compressed into a 2 x 2 second order sub matrix without loosing any significant attributes, primitives, and any other local properties. In stage 2 Fuzzy logic is applied tPo reduce the Gray level range of compressed model of the image. In stage 3 GLCM is derived on SICFRG model of the image. The experimental evidence on FG-NET and Google aging database clearly indicates the high classification rate of the proposed method over the other methods.

KEYWORDS: Significant Features, Grey level – range, five different age groups:

I. Introduction

As humans, we are easily able to categorize a person’s age group from an image of the person’s face and are often able to be quite precise in this estimation. This ability has not been pursued in the computer vision community. In order to begin researching the issues involved in this process, this paper addresses the task of age classification of adult facial image into age groups of 1 to 10, 11 to 20, 21 to 50, 51 to 60 and above 60.

A person’s age is one of the important factors for face recognition, only a few researchers had paid attention to this. One of the most difficult tasks in face recognition and identification is the aging factor. The performance of the above face recognition algorithms significantly degrades as the difference in age between the training face and testing face grows. Any progress in the research community’s understanding of the remarkable ability that human’s have with regard to facial image analysis will go a long way toward the broader goals of face-recognition and facial-expression recognition.

Many methods to handle the aging problem were developed by many researchers. Generation of average faces for different age-groups, using images of subjects with ages between 20 and 62 years were developed using caricature algorithms [1]. Caricature algorithms established two important facts: one is the perceived age of the blended images was consistent with the actual age of the subjects used for generating each composite images; the second factor is that age information for each age-group was retained through the process of blending. Three-dimensional facial information for building a parametric 3D face model is also used as a caricature algorithm in order to exaggerate or deemphasize distinctive 3-D facial features [15, 16]. By this the perceived age was increased or decreased according to the exaggeration level, suggesting that 3D distinctive facial features were emphasized in older face. Choi [5] used PCA and 3-D face shape model to extract the age change components from 3-D facial images, and then added the 'age change' components to test the image to synthesize the facial images at different ages.

A face recognition system, which is robust to age variation, is proposed for building a face model and an age function to isolate age change [12, 13, 14]. Later, automatic age simulation methods for robust face recognition were also proposed [19]. On the age classification problem initially classification of gray-scale facial images into three age groups: babies, young adults, and senior adults were studied [10, 11]. For this purpose, they used deformable templates [21] and snakes [9] to locate primary features (such as eyes, noses, mouth, etc.) from a facial image, and judged if it is an infant by the ratios of the distances between primary features. Later, they used snakes to locate wrinkles on specific areas of a face to analyze the facial image being young or old. Later age classification system based on facial features is used to classify a facial image into one of the four age-groups [8]: babies (0-2), young adults (3-39), middle-aged adults (40-59), and old adults (above 60). In age classification no author used a uniform notation, for example different authors [18, 22] classified age groups differently.

Recently Vijaya kumar V , Chandra Mohan et al developed a new direction for the child and adulthood classification using facial feature parameters derived from geometric properties of human face. The feature parameters of the present approach are computed from facial distance features [2, 3].The adulthood classification methods [2, 3] can be effectively used for persons with folded eye, blind, wearing spectacles, and face images with closed eyes. Further they developed an innovative age classification technique that classifies adult images further with age spans for every ten years based on the topological texture features (TTF) in the facial skin [4].

All these methods performed age classification on entire image. The proposed method is an extension of our earlier method [17], which reduced the image dimensionality to (2N/3 x 2M/3) and achieved a precise stone texture classification. The proposed SICFREG model reduces the image dimensionality further into 2N/5 x 2M/5) and applied on age classification.

There are four publicly available databases that contains face image samples with age wise, namely, the MORPH Database (Ricanek, K. et al. (2006)), the FG-NET Aging Database (http://www.fgnet.rsunit.com/. (2009)), the FERET Database (http://en.wikipedia.org/wiki/feret database. (2009)) and Google database http://images.google.co.in/imghp? hl=en& tab=wi). The MORPH database is the result of an effort to collect a database comprised of longitudinal images of subjects with accompanied physical attribute data (e.g., age at acquisition, weight, height, and ethnicity). It is organized in two albums: MORPH Album 1, which comprises of 1690 digitized images of 515 individuals under the age range 15 to 68 years, and MORPH Album 2 that comprises of 15204 images of nearly 4000 individuals. The FG-NET (Face and Gesture Recognition Research Network) aging database comprises of 1002 images of 82 subjects in the age range of 0 to 69 years. Besides, for any face image, the database provides 68 landmark features manually identified. In addition, some meta information (image size, age, gender, spectacles, hat, mustache, beard, horizontal pose and vertical pose) is also available and there is no control about aspects such as illumination, head pose and facial expressions. The facial aging in the FERET dataset can be divided in three groups: Gallery-set (1196 images), Duplicate I Probe-set (722 images) and Duplicate II Probe-set (234 images). The Google database (http://images.google.co.in/ imghp?hl=en& tab=wi) consists of thousands of randomly chosen facial images. The present paper utilized FG-NET and Google database images, because these are random in nature. This will help to indicate the efficiency and reliability of the proposed and also other methods.

The present paper is organized in the following way. Section 2 handles the methodology. Section 3 handles the experimental results, the section 4 deals with age classification algorithm and comparison with other methods and conclusions in section 5.

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 derivation of SICFRG model consists of 6 steps.

Step 1: 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= $\{P_{11},\ldots, P_{33}, \ldots P_{55}\}$, here P_{33} represents the intensity value of the central pixel and remaining value are the intensity of neighboring pixels as shown in figure 1. Fig 2 represents the formation of nine overlapped 3 x 3 sub neighborhoods represented as {n1, n2, n3,……., n9} from the fig 1.

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}

Fig. 1: 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

Fig. 2: formation of nine overlapped 3 x 3 neighborhoods {n1, n2, n3, …….,, n9} from figure 1.

Step 2: Derivation of First order Local Direction Matrix (FLDM) on the overlapped neighborhoods of 3 x 3 of step one: In the second step, First order Local Direction Matrix (FLDM) is computed for all nine 3×3 overlapped neighborhoods {n1, n2, n3, ……., n9} of step one. 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. The FLDM mechanism is described by the equation (1) and shown in figure 3. This forms nine new 3 x 3 FLDM's and represented as { $FLDM_1$, $FLDM_2$, $FLDM_3$,…….., $FLDM_9$}.

$$FLDM_i = abs\,(P_i - P_c) \text{ for } i = 1,2,\ldots 9 \qquad (1)$$

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

The equation (1) 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. 3: formation of $FLDM_1$ from n1.

STEP 3: Formation of First order Compressed Difference Matrix (FCDM) of size 3 x 3 from 5 x 5: In step three each pixel value of FCDM is evaluated from each of the nine FLDM's of step 2 as given in equation (2). 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.

$$FCDP_i = \text{Avg of } (FLDM_i) \text{ for } i = 1,2,\ldots 9 \qquad (2)$$

Step 4: Formation of Second order Local Direction Matrix (SLDM): In step four SLDM is obtained on the FCDM of step 3 using the equation (3).

$$SLDP_i = abs(FCDP_i - FCDP_c) \text{ for } FCDP_i = 1,2,\dots 9 \quad (3)$$

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

The SLDM matrix is shown in figure 4a. The equation (3) demonstrates that always central pixel value of the 3 x 3 SLDM is zero.

Step 5: : Formation of Second order Compressed Difference Matrix (SCDM) of size 2 x 2 from step four: In step 5 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 figure 4 and as represented in Equations (4), (5), (6), and (7). By this the proposed method reduces the original image of size N×M into the size (2N/5) × (2M/5).

$$SCP_1 = \frac{SLDP_1 + SLDP_2 + SLDP_3}{3} \quad (4)$$

$$SCP_2 = \frac{SLDP_2 + SLDP_3 + SLDP_6}{3} \quad (5)$$

$$SCP_3 = \frac{SLDP_4 + SLDP_7 + SLDP_8}{3} \quad (6)$$

$$SCP_4 = \frac{SLDP_6 + SLDP_8 + SLDP_9}{3} \quad (7)$$

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

(a)

SCP_1	SCP_2
SCP_3	SCP_4

(b)

Figure. 4: Generation process of a SCDM of size 2×2 from a 3 x 3 SLDM neighborhood.
a) The SLDM neighborhood b) SCDM

Step 6: 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 levels in to 5 levels ranging from 0 to 4. That is the reason the derived patterns are named as SICFRG model**.** In LBP binary patterns are evaluated by comparing the neighboring pixels with central pixel. The proposed 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 figure 5. The following equation (8) is used to determine the elements of SICFRG model.

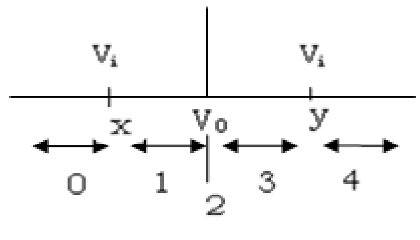

Figure. 5: Fuzzy representation of SCDM model of the image

$$SICFRG_i = \left\{ \begin{array}{l} 0 \text{ if } SCP_i < V_0 \text{ and } SCP_i < x \\ 1 \text{ if } SCP_i < V_0 \text{ and } SCP_i \geq x \\ 2 \text{ if } SCP_i = V_0 \\ 3 \text{ if } SCP_i > V_0 \text{ and } SCP_i > y \\ 4 \text{ if } SCP_i > V_0 \text{ and } SCP_i \leq y \end{array} \right\} \text{for } i = 1, 2, 3, 4 \quad (8)$$

where x, y are the user-specified values.

$$where\ V_0 = \frac{(\sum_{i=1}^{4} SCP_i)}{4} \tag{9}$$

For example, the process of evaluating SICFRG model from a sub SCDM image of 2×2 is shown in figure 6. In this example x and y are chosen as $\frac{V_0}{2}$ and $\frac{3V_0}{2}$ respectively.

28	39
61	9

(a)

1	2
4	0

(b)

Figure. 6: The process of evaluating SICFRG model from SCDM
(a) SCDM (b) SICFRG model.

Step 7: Computation of GLCM features on the derived SICFRG model: The present approach derived Grey level co-occurrence matricx (GLCM) on the SICFRG model of the image for characterization of textures. GLCM is introduced by Haralick [7] attempt to describe texture by statistically sampling how certain grey levels occur in relation to other grey levels. GLCM can measure the texture of the image because co-occurrence matrices are typically large and sparse. From the literature survey, the present study found the *GLCM is a benchmark method for extracting* Haralick features such as [6] angular second moment, contrast, correlation, variance, inverse difference moment, sum average, sum variance, sum entropy, entropy, difference variance, difference entropy, information measures of correlation and maximal correlation coefficient, etc. These features have been widely used in the analysis, classification and interpretation of image data. Its aim is to characterize the stochastic properties of the spatial distribution of grey levels in an image. Haralick [6] extracted 14 parameters from GLCM, where as the novelty of the proposed GLCM features on SICFRG is, it has utilized only three Haralick features i.e energy, entropy and local homogeneity for classification of age into 5 different groups on human faces as given in equation (10) to (12). The proposed SICFRG model with GLCM combines the merits of both statistical and structural information of images and thus represents complete information of the facial image.

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij} \tag{10}$$

$$\text{Energy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij})^2 \tag{11}$$

$$\text{Local Homogenity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \tag{12}$$

III. RESULTS AND DISCUSSIONS

The proposed SICFRG with GLCM features are experimented on a database of the 1002 face images collected from FG-NET database and 500 face images collected from Google database. This leads a total of 1502 sample facial images. Sample images of each group images are shown in figure 7.

Figure. 7: Sample facial images from left to right and top to bottom:-
001A02, 001A10, 009A03, 010A07b, 001A14, 008A13, 009A11, 002A15,
008A29, 004A21, 001A22a, 001A33, 006A40, 006A31, 001A43a, 006A46,
004A48, 006A55, 003A58, 005A52, 006A69, 004A62, 006A67, 003A60.

A. Age group classification by the proposed SICFRG model using GLCM:

The proposed SICFRG model classified the facial images into five age groups 1 to 10, 11 to 20, 21 to 50, 51 to 60 and greater than 60. The three GLCM features i.e energy, entropy and local homogeneity are extracted on SICFRG model of different age groups of facial images and the results are stored in the feature database. Feature set leads to representation of the training images. The three GLCM features of SICFRG facial images of five age groups i.e 1 to 10, 11 to 20, 21 to 50, 51 to 60 and greater than 60 are shown in tables 1, 2, 3, 4 and 5 respectively.

The classification algorithm to classify the facial image is given in algorithm 1. To show the significance of the proposed SICFRG method, probe or test images are taken. On probe image, GLCM features are evaluated on the facial image. Based on the age group classification algorithm, the probe images are tested. For this 40 probe images are collected randomly from various data bases, belonging to various age groups.

Table 1: GLCM feature set values on SICFRG facial images of age group between 1 to 10 years.

S NO	**IMAGE NAME**	**GLCM features on SICFRG model**		
		Energy	**Entropy**	**Homogeneity**
1	001A02	92.4	36.67	128.65
2	010A09	267.89	48.45	145.76
3	001A05	254.91	47.23	162.74
4	001A08	263.69	29.67	154.25
5	001A10	271.75	38.45	149.74
6	002A04	207.23	27.45	174.56
7	002A05	255.21	28.45	173.46
8	002A07	220.57	26.45	189.56
9	009A03	148.27	29.45	192.69
10	009A05	178.18	28.37	81.02
11	009A09	266.43	29.45	179.67
12	010A05	185.18	25.79	175.79
13	010A06	234-94	38.45	178.16
14	010A07a	264.90	37.45	174.56
15	010A07b	262.12	35.78	186.56

Table3: GLCM feature set values on SICFRG facial images of age group between 21 to 30 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	**Entropy**	**Homogeneity**
31	008A29	1567.45	234.56	167.89
32	008A21	1546.29	249.67	138.78
33	006A28	1678.39	236.08	156.67
34	006A24	1768.94	247.67	143.67
35	004A28	1234.78	256.65	159.89
36	004A26	1897.67	234.65	143.67
37	004A21	1786.78	256.67	156.78
38	002A29	1678.79	250.67	178.56
39	002A26	1222.75	221.67	147.78
40	002A23	1289.56	249.67	152.67
41	002A21	1678.93	245.45	158.03
42	001A28	1678.96	219.56	141.98
43	001A29	1567.45	219.67	139.67
44	001A22	1789.27	243.42	154.27
45	009A22a	1891.13	215.68	149.56

Table 2: GLCM feature set values on SICFRG facial images of age group between 11 to 20 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	**Entropy**	**Homogeneity**
16	001A14	645.96	96.56	157.78
17	001A16	744.23	98.56	198.75
18	002A16	799.34	94.45	100.67
19	002A18	865.45	125.56	109.78
20	008A12	700.43	85.67	145.78
21	008A13	698.67	76.44	167.55
22	008A16	856.57	86.24	98.56
23	008A17	878.34	141.75	96.67
24	008A18	902.98	128.40	109.78
25	009A11	564.32	61.67	112.86
26	009A13	697.97	66.30	123.56
27	009A14	675.42	69.90	113.67
28	009A16a	745.79	79.70	156.54
29	009A16b	792.67	76.39	145.78
30	002A15	725.25	77.44	128.56

Table.4: GLCM feature set values on SICFRG facial images of age group between 31 to 40 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	**Entropy**	**Homogeneity**
46	001A33	1267.56	249.96	139.67
47	006A40	2040.04	278.45	98.78
48	006A36	1891.09	296.56	100.01
49	006A31	1578.43	289.56	105.56
50	005A40	1989.67	298.56	124.56
51	005A35	1945.23	202.56	120.45
52	005A31	1356.67	256.67	147.67
53	004A40	2067.34	229.45	108.98
54	004A37	2000.45	278.56	112.34
55	003A38	1945.46	289.67	112.56
56	003A35	1927.45	247.34	134.67
57	002A38	1986.90	299.67	130.34
58	002A36	1561.25	378.45	152.76
59	002A31	1289.93	367.45	123.62
60	007A37	1651.65	324.45	123.97

Table 5: GLCM feature set values on SICFRG facial images of age group between 41 to 50 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	**Entropy**	**Homogeneity**
61	001A43a	1562.27	297.64	57.67
62	013A41	1789.43	298.71	65.79
63	011A42	1289.87	334.65	57.78
64	008A41	1654.78	321.34	45.54
65	007A45	1897.56	345.23	52.45
66	006A46	1673.76	312.56	60.56
67	006A42	1659.45	297.67	59.67
68	005A49	1983.67	378.56	59.67
69	005A48	1567.45	298.45	57.67
70	005A45	1673.78	281.57	55.79
71	004A48	1666.78	313.27	61.45
72	003A49	1455.22	245.56	67.45
73	003A47	1423.56	289.56	59.45
74	001A43b	1564.71	218.24	51.35
75	013A44	1645.45	344.67	67.45

Table. 7: GLCM feature set values on SICFRG facial images of age group above 60 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	Entropy	Homogeneity
1	006A69	2067.67	456.21	10.14
2	003A60	2563.33	432.67	10.52
3	003A61	2871.54	427.89	09.46
4	004A63	2543.69	434.66	11.97
5	004A62	2785.78	435.76	09.82
6	004A63	2553.37	452.44	11.18
7	005A61	2315.89	421.67	11.45
8	006A61	2843.71	465.33	11.22
9	006A67	2951.61	451.48	09.25
10	004A64	2457.52	431.45	10.13

Table.6: GLCM feature set values on SICFRG facial images of age group between 51 to 60 years.

S NO	IMAGE NAME	GLCM features on SICFRG model		
		Energy	Entropy	Homogeneity
1	006A55	1876.56	412.78	22.54
2	003A51	1676.56	406.23	18.56
3	003A58	1896.45	432.67	28.45
4	004A51	1785.78	411.27	19.56
5	004A53	1565.89	412.56	19.78
6	005A52	1784.49	421.09	24.67
7	004A51	1777.77	423.67	22.89
8	006A51	1889.67	421.67	24.01
9	006A51	1989.67	413.41	25.25
10	003A51	1956.45	416.95	20.78

Algorithm 1: Algorithm for Classification of Age in to 5 different groups using GLCM feature on SICFRG model of facial images.

```
Begin
if ( ENTROPHY < 50 )
        print ( facial image age is in between 1-10)
else if (  (ENTROPHY > 50) and (ENERGY < 1000))
        print ( facial image age is in between 11-20 )
else if ( (HOMOGENITY > 15) and (HOMOGENITY < 30 )) and (ENERGY < 2000)
        print ( facial image age is in between 51 to 60)
else if ( HOMOGENITY < 13) and (ENERGY >2000)
    print ( facial image age is > 60 )
else
        print ( facial image age is in between  21-50)
End
```

The algorithm one based on the proposed model classified the facial images into five age groups 1 to 10, 11 to 20, 21 to 50, 51 to 60 and greater than 60 and the classification results are given in table 8.

Table. 8: Classification rates of Age in to 5 different groups using GLCM feature on SICFRG model of facial images based on algorithm.

Image Database	**% correct classification rates by proposed SICFRG Model**
FG-NET ageing database	96.93
Google Images	95.56
Average	96.24

IV. Comparison with other Methods

Though the proposed classification algorithm based on GLCM feature on SICFRG model of facial images is powerful in classification of age groups in to five. Still it is compared with various existing algorithms.

In skin wrinkle geograph map [20] three age groups are classified i.e. child, adults and senior adults, between age groups 1 to 10, 11-60 and above 60 respectively. Since 5 age groups are not classified by [20], the proposed age classification method using GLCM feature on SICFRG model of facial images is modified to classify age groups into three groups in the following way as given in algorithm 2. The classification results by the proposed SICFRG model and skin wrinkle analysis are given in table 9.

Table 9: % mean classification rates for proposed SICFRG model and Cranio-facial development theory and skin wrinkle analysis method.

Image	**Age Groups**	**Cranio-facial development theory and skin wrinkle analysis**	**Proposed SICFRG model**
Child age	1-10	78.15%	96.87%
adults	11-60	79.31%	95.09%
Senior adults	Above 60	81.57%	98.78%

Algorithm 2: Age group classification to classify age into three categories by the proposed SICFRG method

Begin

```
if ( ENTROPHY < 50 )
        print ( facial image age is in between 1-10)
        else if (  HOMOGENITY < 13) and (Energy > 2000)
                print ( facial image age is above 60)
        else
                print ( facial image age is adult’s age)
        END
```

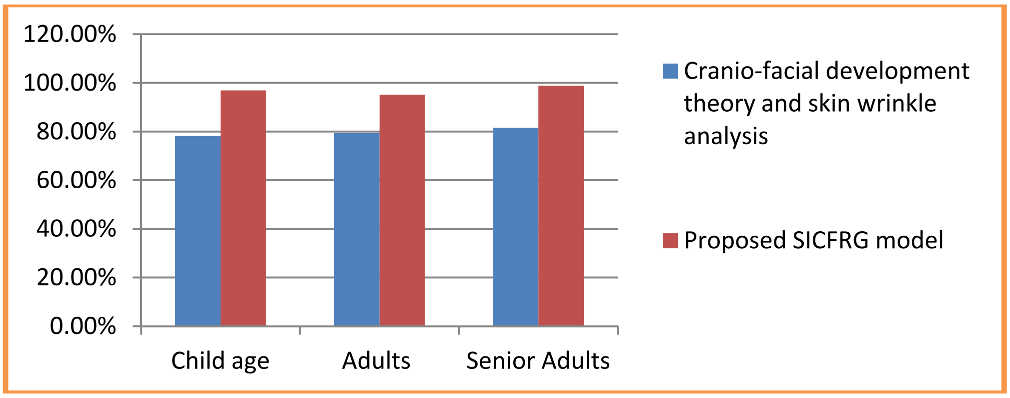

Figure 8: Comparison graph of proposed SICFRG model and cranio-facial development theory and skin wrinkle analysis method

V. Conclusion:

The proposed SICFRG method using GLCM features precisely classified age groups in to five different age groups by reducing the dimensionality and grey level range. The high classification rate clearly indicates the fact that the proposed SICFRG model preserved the all significant local features including edge features, thus it giving a new feature direction to the researchers in the field of texture classification. The proposed method reduced the image dimensionality into 2N/5 x 2M/5. The other advantage of the proposed method is it has used only three haralick parameters for effective precise classifications.

Acknowledgment

I would like to express my cordial thanks to CA. Basha Mohiuddin, Chairman Vidya Group of Institutions, Chevella, R.R.Dt for providing moral support and encouragement towards research, Anurag Group of Institutions, Hyderabad and MGNIRSA, Hyderabad for providing necessary Infrastructure. Authors would like to thank the anonymous reviewers for their valuable comments. And they would like to thank Dr.G.V.S.Ananta Lakshmi, Professor in Dept. of ECS, Anurag Group of Institutions for her invaluable suggestions and constant encouragement that led to improvise the presentation quality of this paper

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AUTHORS PROFILE

J. Sasi Kiran Graduated in B.Tech. (EIE) from JNTU University in 2002. He received Masters Degree in M.Tech. (C&C), 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 Assistant Professor from 2005 to 2007 and working as Associate Professor & HOD in CSE Dept., since 2008 at Vidya Vikas Institute of Technology, Hyderabad. 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.

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 award s from JNTUK Kakinada and Gold plated silver award from Indian Red Cross Society.

Dr. B. Eswara Reddy Graduated in B.Tech(Computer Science and Engineering) from Sri Krishna Devaraya University in 1995. He received Masters Degree in M.Tech. (Software Engineering) from JNT University, Hyderabad, in 1999. He received Ph.D in Computer Science & Engineering from JNT University, Hyderabad, in 2008. He served as Assistant Professor from 1996 to 2006 and as Associate Professor from 2006 to 2012. He is working as Professor of CSE Dept., at JNTUA College of Engineering, Anantapuram since 2012 and currently acting as coordinator for Master of Science in Information Technology (MSIT) programme offered at JNTU Anantapuram. He has more than 50 Publications in various International Journals and Conferences. He is one of the author's of the textbooks titled 'Programming with Java' published by Pearson/Sanguine Publishers and 'Data Mining'published by Elsevier India. His research interests include Pattern Recognition & Image Analysis, Data Mining and Cloud Computing. He is a life member of ISTE, ISCA, Fellow IE (India) and member of CSI and IEEE.