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A novel method for human age group classification based on Correlation Fractal Dimension of facial edges

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Facial image;
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Facial edge image;
Image classification

Abstract In the computer vision community, easy categorization of a person's facial image into various age groups is often quite precise and is not pursued effectively. To address this problem, which is an important area of research, the present paper proposes an innovative method of age group classification system based on the Correlation Fractal Dimension of complex facial image. Wrinkles appear on the face with aging thereby changing the facial edges of the image. The proposed method is rotation and poses invariant. The present paper concentrates on developing an innovative technique that classifies facial images into four categories i.e. child image (0–15), young adult image (15–30), middle-aged adult image (31–50), and senior adult image (> 50) based on correlation FD value of a facial edge image.

1. Introduction

Human facial image analysis has been an energetic and motivating research topic for years. Since human facial image provides a lot of information, interesting research topics are facial image recognition Ahonen et al. (2004), predicting future faces Ahonen et al. (2006), reconstructing faces from some prescribed features Chandra et al. (2009), classifying gender of human being, human facial expressions Atkinson and Lewis (2000) and so on. However, not many studies have been done on human age group classification. In recent years, applications in the area of human communication are 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.

Wen-Bing et al. (2001), considered four age groups for classification, which included babies, young adults, middle-aged adults, and old adults. Their method is divided into three phases: identifying the locations, extracting the features and classification of human age based on extracted features. The method proposed by Kwon and da Vitoria Lobo (1994), is complex in nature and obtained only 81.57% of correct classification. Age group classification on facial images based on the

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crania-facial development theory and skin wrinkle analysis given by Young and Niels-da-Vitoria (1999), considered only three age-groups: babies, young adults, and senior adults. The calculations are done based on the crania-facial development theory and skin wrinkle analysis. While studying physical changes obtained by aging of human beings, many researchers tried to classify facial images into various groups (Todd et al., 1980; Kwon and da Vitoria Lobo, 1994). Sirovich and Kirby (1987) achieved the classification of facial image into two categories, babies and adults. Kosugi (1993) and Hasegawa and Simizu (1997) used neural networks for discriminating facial age generation.

Kazuya Ueki et al. (2006) presented a framework for classification of facial images into age-groups under various lighting conditions which includes *5-year*, *10-year and 15-year range groups*. Sasi Kiran et al. (2013) proposed a Second Order image Compressed and Fuzzy Reduced Grey level (SICFRG) model, which reduces the image dimension and gray level range without any loss of significant feature information. This method classifies the facial image into three categories i.e. child, adults and senior adults. Vijaya Kumar et al. (2014) proposed Topological Texture Features (TTF) of the facial skin that classify the facial image into five categories i.e. 0–12, 13–25, 26–45, 46–60, and above 60. Vijaya Kumar et al. (2013) proposed a method which combines TU and GLCM features by deriving a new model called "Pattern based Second order Compressed Binary (PSCB) image" to classify human age into four groups. Indrajit De et al. (2012) proposed Entropy based fuzzy classification of images on quality assessment.

With the increase of age, wrinkles appear on the face because of changes in internal bone structure, loss of elasticity of the skin and loss of sub cutaneous fat. These factors constitute age-invariant signature from faces. The above changes manifest in the form of changes in facial wrinkles and facial edges. In the proposed approach facial skin wrinkles and internal bone structure of face is considered for the age group classification. So far, no study has attempted to classify the facial image of humans into four categories based on the Fractal Dimension value of the facial skin in various lighting conditions, rotation and pose invariant of human beings. In this work, classification accuracy refers to the percentage of correctly classified facial images.

The rest of the paper is organized as follows. Section 2 describes the proposed age group classification method. Experimental results and comparisons of the results with other methods are discussed in Section 3 and conclusions are given in Section 4.

2. Proposed method

The present paper identified Skin Wrinkle Analysis (SWA) based on wrinkle changes in the facial skin by using facial edge image. This method observed the fact that the facial skin of a person tends to change with growing age. These rapid wrinkle changes in the skin are exploited by edges of facial image. Illumination of image is the most significant factor affecting face appearance besides pose variation, but this paper considers only wrinkle changes not illumination of image because the lighting conditions have less effect on the wrinkle changes and the proposed approach estimates the Fractal Dimensional value of the facial edges which covers the whole face. This paper estimates the Correlation Fractal Dimension (FD) value derived from the facial edge. The block diagram of the proposed method which consists of eight steps is shown in Fig. 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. In step 2, if the images are color images then those are converted into a gray scale facial image using HSV color model. In the third step, the edges of facial image are extracted using the canny edge operator. In the fourth step, the Correlation Fractal Dimension value is calculated. In the last step a new algorithm is derived for an efficient age group classification system based on the Correlation Fractal Dimension.

2.1. RGB to HSV color model conversion

Recent literature reveals various color models in color image processing. In order to extract facial image features from color image information, the proposed method 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 describes more accurately the perceptual color relationship than RGB color space because it is adopted with a non-linear transform. The present paper has used HSV color space model conversion, because the present study is aimed to classify human age into four groups with a gap of 15 years.

HSV color space is created by Hue (H), saturation (S) and value (V). Hue is the property of color such as red, green and blue. Saturation is the intensity of a specific color. Value is brightness of a specific color. However, HSV color space

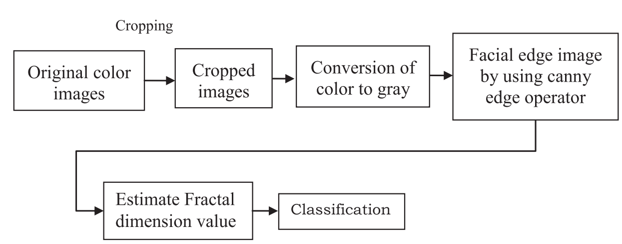

Figure 1 Block diagram for age group classification system.

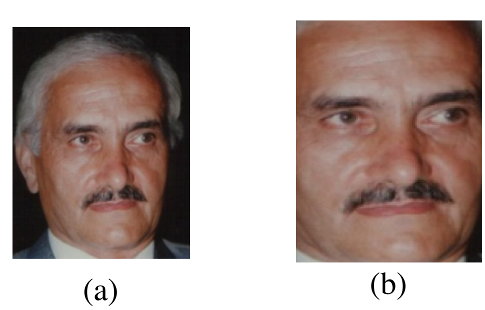

Figure 2 (a) Original image. (b) Cropped image.

separates the color into three categories i.e. hue, saturation, and value. Separation means variations of color observed individually.

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

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

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

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

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

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

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.

1	0	1
-2	0	2
-1	0	1

(a)

1	2	1
0	0	0
-1	-2	-1

(b)

Figure 3 Sobel convolution masks (a) G_x mask (b) G_y mask.

2.2. Generation of facial edge image

Edges are significant local changes of gray values in an image. Typically edges occur on the boundary between two different regions in an image. The facial skin of a person changing with growing age causes gray level value change in facial image. The edges of the same age group have a similar structure. Image edges give good information about the image content because they allow the identification of the object structures. Edge detection is a primary tool used in most of the image processing applications to obtain information from the images as a pioneer step for feature extraction. The edges contain the following features of the image.

1. Identifying coordinates in a digital image at which the image brightness changes sharply or more formally, identifying the discontinuities in an image is the main concept of the edge detection.
2. Edge detection process detects and outlines the boundaries between the foreground and the background in the image.
3. Edge features are useful to overcome the problems generated by noise, edge strips and acuity.
4. Edges form boundaries between the different textures.
5. Edge reveals the discontinuities in image intensity from one pixel to another.

Based on the above features, this paper found that edges are relatively a good choice for obtaining facial image attributes or contents. The facial image edge detection is the process of locating sharp discontinuities in a facial image. The discontinuities are unexpected changes in pixel intensity which differentiate boundaries of objects in a scene. The following features are needed for effective and efficient edge generation.

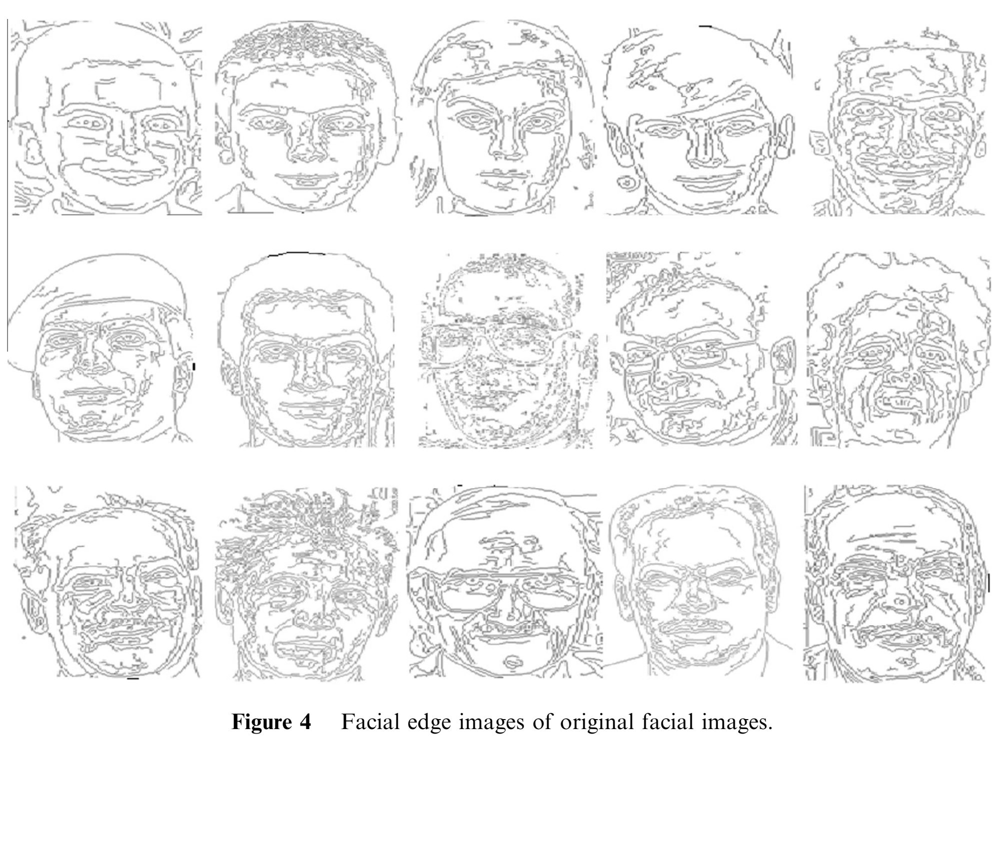

Figure 4 Facial edge images of original facial images.

1. Low error rate: all types of edges must be identified. It should miss the non-edges.
2. Edge points should be well localized: The distance between the pixels of an edge is less when compared with actual facial edge, which is more important in age group classification system.
3. Only one response: it generates to a single edge for image.

To address the above features, the present paper utilizes the canny edge detection algorithm to detect the edges of the facial image (Canny, 1983, 1986; Raman and Himanshu, 2009). The Canny edge detection algorithm is the optimal edge detector.

2.2.1. Canny edge detection procedure for extracting the edges of the facial image

Step 1: Detection of edges effectively by eliminating the noise in the facial image using Gaussian filter. The size of the convolution mask is usually much smaller than the size of the actual image.

Step 2: Calculation of the gradient of the image which is used to find out the edge strength of the facial image. To calculate approximate absolute gradient magnitude (edge strength) at each point, the Sobel operator is used. The Sobel operator Matthews (2002) uses two 3×3 masks, one for estimating the gradient in the x-direction (columns) and the other for estimating the gradient in the y-direction (rows). The 3×3 masks are shown in Fig. 3. The gradient is calculated using the formula shown in Eq. (6):

$$|G| = |G_x| + |G_y|. \tag{6}$$

Step 3: The gradient is used for finding direction of the edge in the x and y directions. If gradient G_x is equal to zero then the edge direction is either 0 or 90 degrees depending upon the value of the gradient in the y-direction. If G_Y is equal to zero, then the edge direction will be equal to 0° otherwise the edge direction will equal 90°. The equation used for finding the edge direction is shown below:

$$Theta = \tan^{-1}\left(\frac{G_y}{G_x}\right) \tag{7}$$

Step 4: The process of finding the edge direction, to a direction that can represent edge in an image.

Table 1 Correlation Fractal Dimension values of child age images.

S.No.	Image name	Correlation Fractal Dimension value
1	001A05	1.412749
2	001A08	1.441561
3	008A12	1.441974
4	001A14	1.456928
5	001A02	1.450087
6	001A10	1.448903
7	002A04	1.445278
8	002A05	1.444731
9	002A07	1.452915
10	002A12	1.441456
11	002A15	1.436752
12	009A00	1.445372
13	009A01	1.438303
14	009A03	1.429803
15	009A05	1.442132
16	009A09	1.436746
17	009A11	1.442707
18	009A13	1.440525
19	009A14	1.434774
20	010A01	1.438029
21	010A04	1.445650
22	010A05	1.450909
23	010A06	1.441160
24	010A07a	1.429268
25	010A07b	1.438912
26	010A09	1.430369
27	010A10	1.438735
28	010A15	1.444915
29	011A02	1.452414
30	010A12	1.441160

Figure 5 Sample images of FG-Net aging database.

Step 5: After the edge directions are found then non-maximum suppression operations are to be applied. While the edge is traced, edge direction suppresses the pixels whose pixel value is zero (which is not considered as an edge). The process of eliminating pixels is called Non-maximum suppression. The result of non-maximum suppression generates thin line in the output edge image.

Step 6: Because of fluctuating threshold there is a chance for breaking an edge contour called streaking. The streaking is eliminated using hysteresis given by Canny (1983).

Plastic surgery also plays a basic role of the age interval. This factor reduces the age group classification percentage. The proposed approach also solves that problem. In the proposed approach the edge of the facial image is considered. These edges are generated based on wrinkle changes and also the internal bone structure of the facial image. Through plastic surgery the skin is tightened, but the internal bone structure and muscle tissue remain the same. The resultant facial edge images generated using the above procedure are shown in Fig. 4 below.

The variances are not completely independent with respect to their spatial positions, but their correlation depends on the distance. Especially facial edges are characterized by nearly repeating patterns and therefore some periodicities are often identified. A fractal dimension is a ratio providing a statistical index of complexity comparing how detail a fractal pattern changes with the scale at which it is measured. It has also been characterized as a measure of the space-filling capacity of a pattern that tells how a fractal scales differently from the space it is embedded in. Hence calculating the fractal dimension using a multi layered grid of the facial edges is giving correct classification results.

2.3. Calculate the fractal dimension value

Fractals are geometric primitive such as self-similar and irregular in nature. Fractal Geometry was introduced by Mandelbrot in 1982. Both a mathematical model and a description for many of the seemingly complex forms found in nature can be provided by fractal models given by Mandelbrot (1982). The Correlation Fractal Dimension (FD) is the defining characteristic of a fractal which has been used as a measure of spatial complexity. The fractal-based methods have been applied to many areas of digital image processing, such as, image synthesis, image compression and image analysis (Fournier et al., 1982; Pentland, 1984; Barnsley, 1988; Tao et al., 1990). No one has attempted to classify the facial images into various age groups using fractal dimension. The present paper utilizes the fractal geometry for classifying the facial edge image into four categories such as child (0–15), young

Table 2 Correlation Fractal Dimension values of young age images.

S.No.	Image name	Correlation Fractal Dimension values
1	001A16	1.463837
2	001A19	1.485844
3	001A29	1.467502
4	002A16	1.484007
5	001A18	1.462510
6	001A22	1.479858
7	001A28	1.479865
8	002A18	1.483371
9	002A20	1.486882
10	002A21	1.476023
11	002A23	1.475164
12	002A26	1.472515
13	002A29	1.474010
14	004A19	1.475325
15	004A21	1.471641
16	004A26	1.473497
17	004A28	1.474268
18	004A30	1.469356
19	005A18	1.471830
20	005A24	1.462689
21	005A30	1.468497
22	006A24	1.460503
23	006A28	1.489177
24	007A18	1.469181
25	007A22	1.475848
26	007A23	1.470934
27	007A26	1.477601
28	008A17	1.467170
29	008A29	1.482511
30	008A30	1.478497

Table 3 Correlation Fractal Dimension values of middle age images.

S.No.	Image name	Correlation Fractal Dimension value
1	001A43a	1.524977
2	002A31	1.510929
3	002A38	1.524977
4	003A35	1.520141
5	003A47	1.516743
6	003A49	1.530470
7	001A43b	1.517953
8	001A33	1.507953
9	001A40	1.517800
10	003A47	1.490996
11	002A36	1.505634
12	003A38	1.514186
13	004A37	1.506948
14	004A40	1.517417
15	004A48	1.521465
16	006A31	1.510929
17	006A36	1.524977
18	006A40	1.510929
19	006A42	1.516949
20	006A44	1.515305
21	006A46	1.522557
22	006A48	1.535962
23	006A50	1.523905
24	008A41	1.510929
25	008A43	1.517375
26	008A45	1.505946
27	008A47	1.520141
28	011A34	1.505946
29	011A40	1.500962
30	011A42	1.510929

adults (15–30), middle-aged adults (31–50), and senior adults (> 50).

For describing the characteristics of the image, different visual appearances based on wavelets and multi-resolution analysis have the same fractal dimension value. The fractal-dimension based methods have been applied to many areas of digital image processing, such as image analysis Paul (2005) which demonstrated fractal dimension for natural images is not sufficient for description of images. To address the above problems, Correlation Fractal Dimension value is calculated on the edges of the facial image. The important characteristic of fractals is fractal dimension because it has got information about their geometric structure. The topological dimension value of an image would not change whatever be the transformation of an image.

Correlation Fractal Dimension value is estimated using algorithm given by Anuradha et al. (2013). In a bounded Euclidean n-space, consider a self-similar set X in the range of scales ($r_{\min}$, $r_{\max}$), the Correlation Fractal Dimension D_2 as described by Belussi and Faloutsos (1995) can be derived from the following Eq. (8). The self-similar set X is the union of N_r distinct non-overlapping copies of itself, each of which is similar to X scaled down by a ratio r. The algorithm for computation of Correlation Fractal Dimension is shown in Algorithm 1.

$$D_2 = \frac{\partial \log \sum_i C_{r,i}^2}{\partial \log r}, r \in [r_{\min}, r_{\max}] \tag{8}$$

where $C_{r,i}$ is the occupancy with which the pixel falls in the ith cell when the original space is divided into grid cells with sides of length r.

Algorithm 1. Computation of Fractal Dimension

Step 1: Read a 2-Dimensional facial edge image (FI)
Step 2: Find the size of the Image i.e. number of Rows (R) and Columns (C)
Step 3: if R is greater than C, r is assigned to R otherwise r is assigned to C
Step 4: Compute the Correlation Fractal Dimension value using Eq. (8).

End

The algorithm for age group classification using Correlation Fractal Dimension is shown in algorithm 2

Table 4 Correlation Fractal Dimension values of senior adults' images.

S.No.	Image name	Correlation Fractal Dimension value
1	003A51	1.571369
2	003A53	1.587708
3	003A58	1.545771
4	003A60	1.566048
5	003A61	1.575224
6	004A51	1.581423
7	004A53	1.578723
8	004A55	1.578723
9	004A57	1.546702
10	004A62	1.570718
11	006A55	1.564714
12	003A60	1.544913
13	004A63	1.601423
14	006A61	1.556024
15	006A69	1.601410
16	003A57	1.575058
17	004A55	1.570718
18	004A57	1.576312
19	004A59	1.556024
20	004A61	1.553836
21	004A63	1.578723
22	004A65	1.588176
23	004A67	1.568723
24	004A69	1.590073
25	006A51	1.575974
26	006A54	1.575073
27	006A57	1.584398
28	006A60	1.576280
29	006A63	1.562713
30	006A66	1.574447

Table 5 Successful results of tested database.

S.No.	Image name	Correlation Fractal Dimension value	Classified age group	Results
1	001A08	1.437655	0–15	Success
2	002A18	1.472394	16–30	Success
3	003A20	1.455458	16–30	Success
4	005A24	1.472374	16–30	Success
5	063A05	1.442735	0–15	Success
6	064A16	1.464567	16–30	Success
7	064A59	1.574029	> 50	Success
8	065A03	1.424591	0–15	Success
9	067A18	1.467672	16–30	Success
10	022A28	1.482954	16–30	Success
11	023A29	1.520294	31–50	Success
12	024A30	1.441616	0–15	Success
13	025A48	1.514487	31–50	Success
14	027A30	1.476059	16–30	Success
15	017A62	1.586285	> 50	Success
16	018A34	1.522451	31–50	Success
17	020A36	1.523599	31–50	Success
18	025A59	1.582324	> 50	Success
19	Sci-1	1.518271	31–50	Success
20	Sci-2	1.448279	0–15	Success
21	Sci-3	1.464794	16–30	Success
22	Sci-4	1.484569	31–50	Fail
23	Sci-5	1.574232	> 50	Success
24	Sci-6	1.441062	0–15	Success
25	Sci-7	1.436402	0–15	Success
26	Sci-8	1.571147	> 50	Success
27	Sci-9	1.456588	16–30	Success
28	Sci-10	1.435214	0–15	Success
29	Sci-11	1.503605	31–50	Success
30	Google-img-001	1.435968	0–15	Success
31	Google-img-002	1.515277	31–50	Success
32	Google-img-003	1.515612	31–50	Success
33	Google-img-004	1.568283	> 50	Success
34	Google-img-005	1.505946	31–50	Success
35	Google-img-006	1.560115	> 50	Success
36	Google-img-007	1.441616	0–15	Success
37	Google-img-008	1.578482	> 50	Success
38	Google-img-009	1.493373	16–30	Fail
39	Google-img-010	1.562861	> 50	Success
40	Google-img-011	1.568050	> 50	Success

Algorithm 2. Age group classification using Correlation Fractal Dimension

Step 1: Take facial image as Input Image (Img)
Step 2: Crop the image
Step 3: Convert the RGB image into Gray scale Image using HSV color model
Step 4: Extract the edge image of facial gray scale image using canny edge detection
Step 5: Calculate the FD values using the algorithm 1
Step 6: Based on the fractal dimension value of the facial image (FDV) , the image is classified as child (0–15), young adults(16–30), middle-aged adults(31–50), and senior adults(> 50)
if (FDV < 1.46) , facial image age is Child (0–15)
if FDV is between 1.46 and 1.49 , facial image age is young age (16–30)
if FDV is between 1.49 and 1.54 , facial image age is middle-age (31–50)
else facial image age is senior age (> 50)
Step 2: end.

3. Results and discussions

The proposed scheme established a database from the 1002 facial images collected from FG-NET database, 500 images from Google database and other 600 images collected from the scanned photographs. This leads a total of 2102 sample facial images. The proposed method considers 20 age variations of the each facial image on different age groups from one year to old age. The database consists 2012 with 20 age variations of each image leading to a total of 40240 images. Another important aspect in this proposed approach is calculation of the FDV value of the facial image with 8 different orientations i.e. 0, 45, 90, 135, 180, 225, 270, 315 degrees. So the proposed approach is also rotational invariant age group classification system. Totally 321920 images are considered for proving the proposed approach classifies the facial images into various age groups. In the proposed method the sample images are grouped into four age groups of child age (0–12), young age (13–30), middle age (31–50) and senior age (51–70). A few of them are shown in Fig. 5. The fractal dimension values of four age groups of some of facial images are shown in Tables 1–4 respectively. The minimum and maximum correlation FD values of the each category are represented using scatter diagram in Fig. 6. Based on the derived values on facial images an algorithm is derived by the present paper to classify the facial image into one of the categories of child age (0–12), young age (13–30), middle age (31–50) and senior age (51–70) and it is shown in algorithm 2. The classification graph of age group classification based on the proposed method is shown in Fig. 7. To evaluate the accuracy, and significance of the present method probe or test images are taken. On probe image, the Correlation Fractal Dimension on the facial image is calculated. As an experimental case 40 face samples, randomly collected from FG-NET, Google database and some Scanned images, with Correlation Fractal Dimension value on the facial images with their successful classification

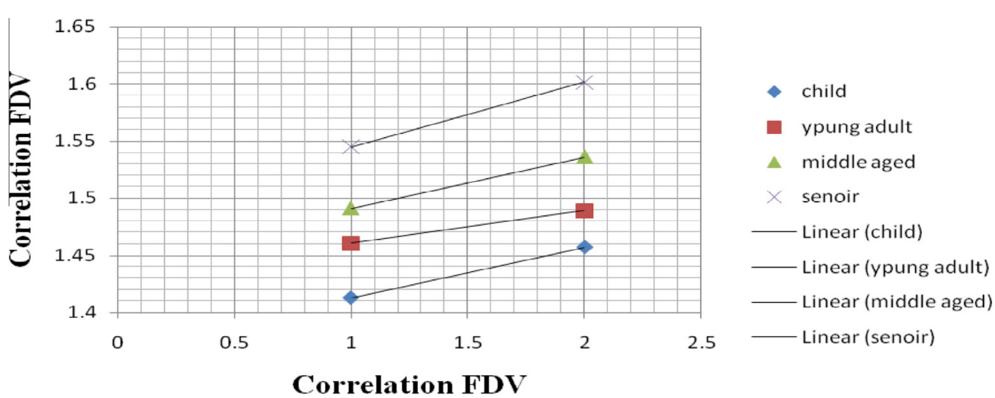

Figure 6 Scatter diagram of the four categories.

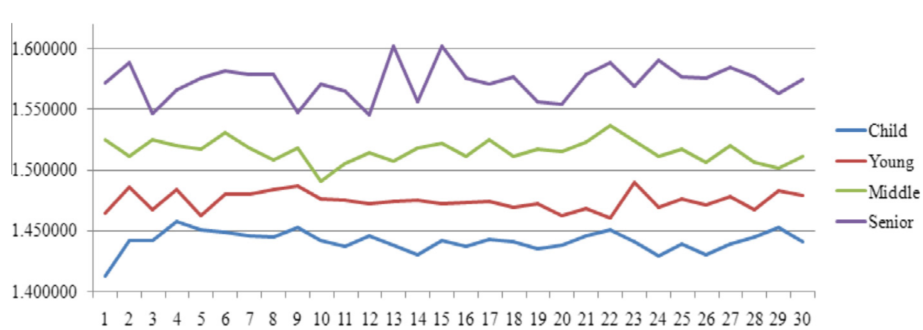

Figure 7 Classification graph of age group classification based on the proposed method.

results using present scheme are given in Table 5. The classification percentage of three datasets is shown in Table 6 and the classification graph of three datasets are shown in Fig. 8. Whenever age grows wrinkles are formed and those wrinkles are changed with respect to the age of a person. For young aged persons wrinkles are almost negligible, for middle aged persons considerable wrinkle changes are formed and for senior aged people year by year wrinkles are changed so more wrinkle changes are clearly identified for senior aged people. In this proposed method the authors considered wrinkle changes on the facial image of the front area of the image i.e. from fore head to chin area. The Hair area of the facial image is removed in the cropping step of the proposed method. The proposed method is giving good results because it considers full face of humans which includes all features i.e. the shape of eyes, nose, mouth, chin and pose of the facial image. The proposed technique is successful in categorizing the age group and overall average classification percentage is 99.16.

The proposed method gives the best % mean classification rates because of the calculation of single feature value. The single feature value is not changed for a particular image even though the image is rotated and pose of the image is changed. This value changes only if age of the person changes thereby changing the FDV value. From Fig. 6 it is observed that when the age grows FDV also increased.

Table 6 Successful classification rates of the three databases.

Image Dataset	FG-NET database (%)	Google database (%)	Scanned images (%)	Average (%)
Child	100.00	100.00	100.00	100.00
Young adults	100.00	97.50	97.50	98.33
Middle adults	100.00	100.00	97.50	99.17
Senior adults	100.00	97.50	100.00	99.17
Mean percentage	100.00	98.75	98.75	99.17

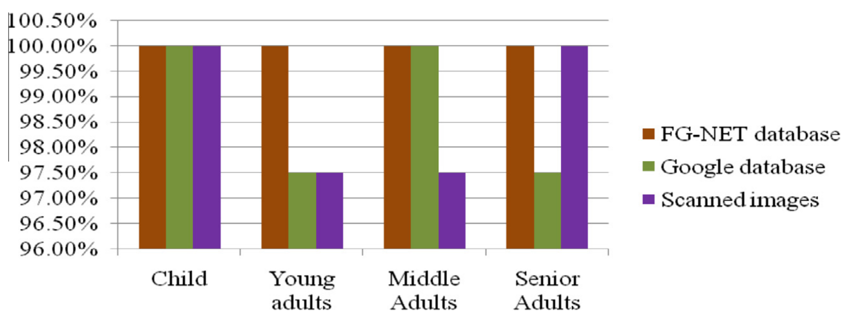

Figure 8 Classification graph of three datasets.

Table 7 % mean classification rates for proposed method and other existing methods.

Image dataset	Identification of facial parts and RBF neural network	Geometric properties (%)	Morphological primitive patterns with grain components on LDP (%)	Proposed method (%)
Child	89.67	91.04	92.17	100.00
Young adults	85.3	92.71	93.37	98.33
Middle adults	88.72	90.07	92.56	99.17
Senior adults	87.9	92.10	92.40	99.17

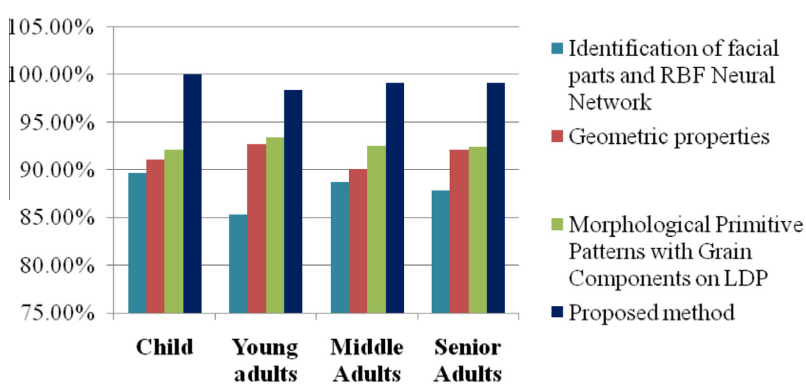

Figure 9 Comparison graph of proposed method with other existing methods.

4. Comparison of the proposed method with other existing methods

The proposed method of age classification is compared with the existing methods (Wen-Bing et al., 2001; Sujatha et al., 2011; Yazdi et al., 2012). The method proposed by Yazdi et al. (2012) identified facial image using RBF Neural Network Classifier. The method proposed by Wen-Bing et al. (2001) is based on two geometric features and three wrinkle features of facial image. The method proposed by Sujatha et al. (2011) classifies the facial image into either child or adult based on Primitive Patterns with Grain Components on Local Diagonal Pattern (LDP). The percentage of classification of the proposed method and other existing methods is listed in Table 7. The graphical representation of the percentage mean classification rate for the proposed method and other existing methods is shown in Fig. 9.

5. Conclusions

The present paper developed a new direction for age group classification using Correlation Fractal Dimension value on edge of human face. The proposed method extracts the edges of the facial images using canny edge detection algorithm. The canny edge detection is more helpful for age group classification as it detects the edges very clearly and differentiates with other edges. So far fractal geometry is not used for classification because single fractal dimension is not enough for the description of natural images. But through this paper authors projected a novel method demonstrating that fractal geometry is also a good measure for classification. This method proves that efficient classification depends on the type of feature extracted on an image not on the number of features extracted on an image. The present method is tested on three datasets namely FG-NET aging database, Google Images and Scanned images with different orientations and with different lighting conditions. The performance of the present system is more effective for the FG-NET aging database when compared with Google Images and scanned images.

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