A Comparative Study of Fractal Dimension Based Age Group Classification of Facial Images with Different Testing Strategies

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Abstract. The demand of estimation of age from facial images has tremendous applications in real world scenario like law enforcement, security control, and human computer interaction etc. However despite advances in automatic age estimation, the computer based age classification has become prevalent. The present paper evaluates the method of age group classification based on the Correlation Fractal Dimension (FD) of facial image using different validation techniques. To reduce variability, multiple rounds of cross validation are performed using different partitions to the data. The expected level of fit of the model classifying facial images into four categories based on FD value of a facial edge is estimated using multiple cross-validation techniques. The simulation is carried out and results are analyzed on different images from FG-NET database, Google database and from the scanned photographs as these are random in nature and help to indicate the efficiency and reliability of the proposed method. It is also a successful demonstration that Correlation Fractal Dimension of a facial edge is sufficient for a classification task with high percentage of classification accuracy.

Keywords: Age Group classification, Correlation Fractal Dimension, facial image, canny edge, facial edge image, cross validation.

1 Introduction

Automatic age estimation and predicting future faces have rarely been explored. With human age progression face features changes. Humans can identify very informative facts from facial images, which include identifying, age, gender etc. The identification of different features of face images has been well explored in real-world applications [1], including passports and driving licenses. Despite the broad exploration of person identification from face images, there is only a limited amount of research [2] on how to accurately estimate and use the demographic information contained in face images such as age, gender, and ethnicity. This laid foundation for interesting research topics on gender classification [3], facial image recognition [4], predicting future faces [5], and reconstructing faces from specified features [6] and so on. As human age

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estimation supports many potential application areas, identification of age by computers has become prevalent. Fu and Huang [7] estimated the age on the holistic appearance of the image. Chao et al. [8] made classification based on Label-sensitive relevant component analysis and Chang et al. [9] considered Ordinal hyper plane ranking. A hierarchical age estimator [10] is proposed for automatic age estimation. Age groups for classification including babies, young adults, middle-aged adults, and old adults is given by Wen-Bing et al.,[11]. Age group classification on facial images based on crania-facial development theory and skin wrinkle analysis [12], considered only three age-groups babies, young adults, and senior adults. The calculations are done based on crania-facial development theory and skin wrinkle analysis. While studying physical changes obtained by ageing of human being, many researchers tried to classify facial images into various groups [13]. Sirovich and Kirby [14] classified images into two categories, babies and adults. Neural networks are used for discriminating facial age generation [15][16]. Classification of Facial image of human into four categories based on Fractal Dimension value of the facial skin [17] is a new concept developed and this paper focuses on finding the accuracy of the model based on different test strategies. In this paper the focus is on studying the efficiency of the proposed method [17], Correlation Fractal Dimension based age group classification using multiple cross validation techniques. Different testing and validation techniques such as hold out method and tenfold cross validation method are investigated and the comparison analysis is presented. From the simulation it is observed that our proposed method [17] passes with good classification efficiency through rigorous methods of testing successfully and hence robust in nature.

The rest of the paper is organized as follows. Section 2 deals the proposed age group classification method. Different cross validation techniques and their results are discussed in section 3 and section 4 presents conclusions.

2 Proposed Method

Age group classification of the proposed method [17] is done by using facial edge of an image. The rapid wrinkle changes in the skin are exploited by edges of facial image. The following steps are proposed to estimates the Correlation Fractal Dimension (FD) value derived from the facial edges.

Step 1: Consider the original color image
Step 2 : Original image is cropped based on the location of the eyes
Step 3: Cropped image is converted to a gray scale image
Step4: Facial edges of the gray scale image are extracted as given in Fig 1.
Step 5: Estimate the fractal dimension value of the facial edge of an image
Step 6 : Classify the age group of the facial image based on the correlation fractal dimension

The original facial image is cropped based on the two eyes location in the second step. In the step 3, if the images are color images then those are converted into a gray scale facial image by using HSV color model. In the fourth step, extract the edges of facial image by using canny edge operator. In the fifth step, calculate the Correlation

Fractal dimension value. In the last step a new algorithm is derived for an efficient age group classification system based on the Correlation Fractal Dimension.

Recent literature revel 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 proposed method uses HSV color space model conversion, because the present study is aimed to classify the human age in to four groups with a gap of 15 years.

This paper [17] 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 paper [17] utilizes the canny edge detection algorithm to detect the edges of the facial image [18][19][20] The Canny edge detection algorithm is the optimal edge detector.

2.1 Calculate the Fractal Dimension Value

Fractal is self-similar objects. Inherently, fractals also have a degree of self-similarity. This means that a small part of a fractal object may resemble the entire fractal object. Fractals are Geometric primitive such as self-similar and irregular in nature. Fractal Geometry was introduced by Mandelbrot [21]. The correlation fractal dimension (FD) is the defining characteristic of a fractal which has been used as a measure of similarity. The fractal- based methods have been applied to many areas of digital image processing, such as, image synthesis, image compression and image analysis [22][23]. The present paper analyses the results more extensively on the method for classifying the facial edge image into four categories such as child (0-15), young adults (15-30), middle-aged adults (31-50), and senior adults (> 50)[17].

Fig. 1. Facial edge images of original facial images

Many application areas of digital image processing used fractal dimension [24] and demonstrated that finding the fractal dimension on colored images is not giving better results for classification and hence in the proposed method [17] correlation fractal dimension value, is calculated on edges of the facial image which proved to give better results. Correlation Fractal Dimension value is estimated using algorithm given by [25]. Given a dataset that has the self-similarity property in the range of scales [r1, r2], its Correlation Fractal dimension D2 for this range is measured as given in following equation 1. The algorithm for computation of Correlation Fractal Dimension is shown in Algorithm 1.

$$D_2 = \frac{\partial \log \sum_i S_{r,i}}{\partial \log r}, \mathrm{r} \in [\mathrm{r1}, \mathrm{r2}] \tag{1}$$

Where $S_{r,i}$ is the squared sum of occupancy with which the pixel fall in the ith cell when the original space is divided into grid cells with sides of length r.

Algorithm 1 : Computation of Fractal Dimension [17]

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 the equation 1.
End

The algorithm for age group classification using correlation fractal dimension is shown in algorithm 2

Algorithm 2: Age Group Classification Using Correlation Fractal Dimension

Let fractal dimension value is treated as FDV

```
if ( FDV < 1.46 )
        print (facial image age is Child ( 0-15))
else if ( FDV < 1.49 )
        print (facial image age is Young age(16-30))
else if ( FDV < 1.54 )
        print (facial image age is middle-age(31-50))
else
        print (facial image age is Senior age(> 50))
end.
```

3 Results and Discussions

The objective of our classification is to categorize the images of the dataset into four different categories based on age where the child class is between 0 and 15 years, Young Age is between 15 and 30 years, Middle Age from 31 to 50 years and Senior Age is above 50 years. This section projects the detailed presentation of the results obtained using different cross validation techniques. The images for age group classification are collected from multiple data sources like 1002 facial images from FG-NET database, 500 images from Google database and 600 images from the scanned photographs leading to a total of 2102 sample facial images. A few of them are shown in Fig 2. FG-NET consists of 1,002 images of 82 individuals. The average number of images per individual is 12. Although the age of subjects in FG-NET ranges from 0-69 years, over 50% of the subjects in FG-NET are between the ages 0 and 13.The Google database consists of thousands of randomly chosen facial images.

Fig. 2. Sample images of FG-Net aging database

To prove the efficiency of the proposed method the results are tested with hold out and tenfold cross validation testing strategies

3.1 Hold Out Result Analysis Method (HORM)

In Hold Out Result Method (HORM) the total 2102 images are divided into two sets where two third for training the algorithm and one third for testing. Training set consists of 700 FG-Net aging data base, 300 images from Google and 400 images collected from scanned images leading to a total of 1400 images for which FD values are calculated using the algorithm 1. Second set consists of 302 images from FG-Net database, 200 images from Google and 200 images from scanned photographs, totally 702 images. Second set is treated as a test database where the correlation fractal dimension values is found to classify the images based on the proposed algorithm [17]. The classification results of the FG-Net ageing, Google and scanned images in the test database are listed out in the tables 1, 2 and 3 respectively. The classification graph of the test database in Hold out method is shown in figure 3. From HORM method it is observed that middle aged human faces got 100 percentage classifications irrespective of image. The FG-Net ageing database got 100% classification results in all categories. In HORM, Scanned images got low percentage of classification due to poor quality of the scanned images.

Table 1. Classification results of the FG-NET database

Category	Total	Correctly classified	FG-NET database not correctly classified	% of Classification
Child	89	89	0	100
Young adults	67	67	0	100
Middle Adults	85	85	0	100
Senior Adults	61	61	0	100

Table 2. Classification results of the Google database

Category	Total	Correctly classified	Google database not correctly classified	% of Classification
Child	43	42	1	97.67
Young adults	59	59	0	100
Middle Adults	45	45	0	100
Senior Adults	53	52	1	98.11

Table 3. Classification results of the Scanned image database

Category	Total	Correctly classified	Scanned images not correctly classified	% of Classification
Child	56	56	0	100
Young adults	51	50	1	98.03
Middle Adults	47	47	0	100
Senior Adults	46	45	1	97.8

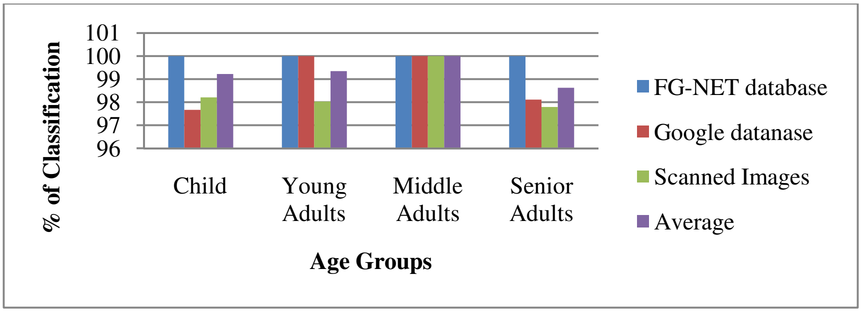

Fig. 3. Classification graph of the Hold out method

3.2 Ten Fold Cross Validation Method (TFVM)

In TFVM results analysis method, the entire 2102 images are divided into ten data sets, every time nine subsets are taken for calculating FD during our training phase and one subset is used for testing. In this process each and every subset is considered while training. The classification accuracies are separately computed in each round and finally the algebraic average of ten rounds are presented as percentage of correct classification. Each set consists of 210 images of four categories facial images i.e. Child, Young adults, Middle Adults, senior Adults from FG-Net, Google, and scanned images. Form this analysis we strengthen the proposed algorithm. The classification results of the proposed method in ten rounds are evaluated and are listed out in tables 4 to 13 respectively. The overall classification results of the TFVM are listed out in table 14 and corresponding round wise classification graph in shown in figure 4.

Table 4. Classification results of proposed method in round 1 of TFVM

		Round 1		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	46	45	1	97.82
Young adults	43	43	0	100
Middle Adults	64	64	0	100
Senior Adults	57	56	1	98.24

Table 5. Classification results of proposed method in round 2 of TFVM

		Round 2		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	46	45	0	100
Young adults	43	42	1	97.67
Middle Adults	64	64	0	100
Senior Adults	57	56	1	98.24

Table 6. Classification results of proposed method in round 3 of TFVM

		Round 3		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	66	66	0	100
Young adults	48	47	1	97.91
Middle Adults	51	50	1	98.03
Senior Adults	45	45	0	100

Table 7. Classification results of proposed method in round 4 of TFVM

Category	Total	Round 4 Correctly classified	not correctly classified	% of Classification
Child	66	65	1	98.48
Young adults	37	36	1	97.29
Middle Adults	47	46	1	97.87
Senior Adults	60	59	1	98.33

Table 8. Classification results of proposed method in round 5 of TFVM

Category	Total	Round 5 Correctly classified	not correctly classified	% of Classification
Child	39	39	0	100
Young adults	43	42	1	97.67
Middle Adults	58	58	0	98.28
Senior Adults	74	73	1	98.65

Table 9. Classification results of proposed method in round 6 of TFVM

Category	Total	Round 6 Correctly classified	not correctly classified	% of Classification
Child	38	37	1	97.36
Young adults	47	46	1	97.87
Middle Adults	74	73	1	98.67
Senior Adults	51	51	0	100

Table 10. Classification results of proposed method in round 7 of TFVM

Category	Total	Round 7 Correctly classified	not correctly classified	% of Classification
Child	62	62	0	100
Young adults	53	53	0	100
Middle Adults	45	45	0	100
Senior Adults	50	49	1	98.00

Table 11. Classification results of proposed method in round 8 of TFVM

		Round 8		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	48	47	1	97.96
Young adults	56	55	1	98.25
Middle Adults	61	60	1	98.36
Senior Adults	45	44	1	97.77

Table 12. Classification results of proposed method in round 9 of TFVM

		Round 9		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	52	51	1	98.11
Young adults	47	46	1	97.87
Middle Adults	46	46	0	100
Senior Adults	65	64	1	98.46

Table 13. Classification results of proposed method in round 10 of TFVM

		Round 10		
Category	Total	Correctly classified	not correctly classified	% of Classification
Child	60	59	1	98.36
Young adults	51	51	0	100
Middle Adults	42	41	1	97.67
Senior Adults	57	56	1	98.28

Table 14. Overall % Classification of TFVM method

Category	Total	Correctly classified	not correctly classified	% of Classification
Child	522	516	6	98.85
Young adults	468	461	7	98.50
Middle Adults	552	547	5	99.09
Senior Adults	560	553	7	98.75
Total	2102	2077	25	98.81

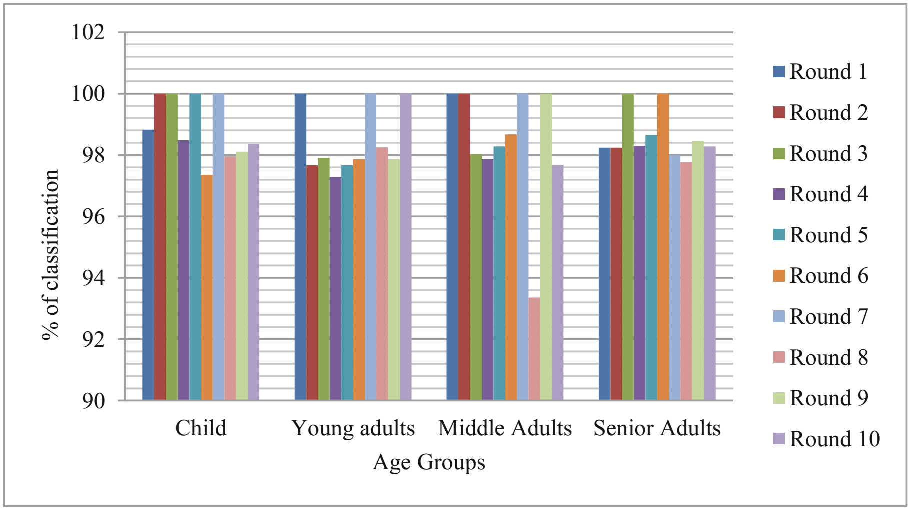

Fig. 4. Round wise classification graph of TFVM method

Comparison of the Proposed Method with Other Existing Methods

The proposed method of age classification is compared with the existing methods [26][11][27]. The method proposed in [27] identified facial image using RBF Neural Network Classifier. The method proposed in [11] is based on two geometric features and three wrinkle features of facial image. The method proposed in [26] classifies the facial image into either child or adult based on Primitive Patterns with Grain Components on Local Diagonal Pattern (LDP). The graphical representation of the percentage mean classification rate for the proposed method and other existing methods are shown in Fig.5.

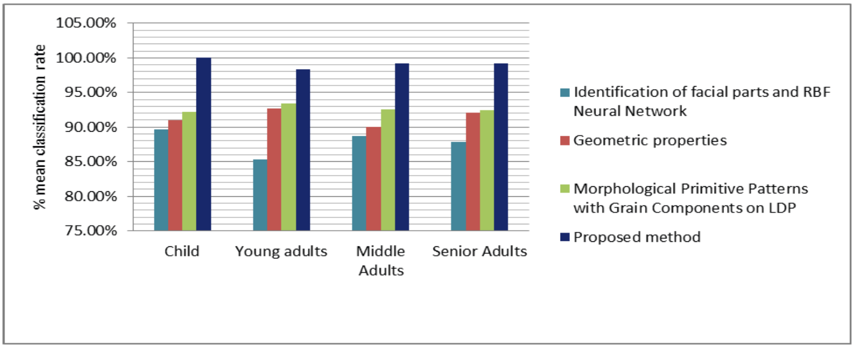

Fig. 5. Comparison graph of proposed method with other existing methods

4 Conclusions

In this paper the results obtained using random testing [31] strategy is found to match well with other two strategies studied here. In all the three strategies the percentage of correct classification is very close to each other in all the considered data sets. For example the mean correct classification in random testing [31] is 99.19 and hold out method is 98.89 and Ten fold testing is 98.85 .The mean standard deviation of all the methods is 0.185. From the above discussion it can be clearly observed that our proposed algorithm based on correlation fractal dimension to detect age from facial images is a robust algorithm. This claim is proved from the analysis of percentage of correct classification using different testing strategies. The performance of the present system is more effective for the FG-NET aging database when compare with Google Images and scanned images. Our method can be further extended for images with noise.

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