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Research paper

Facial age estimation using SFTA and deep neural network

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Abstract

This paper construes the toils in facial age estimation in images. The fact that manual age estimation is indeed hard rising out the urge for digital age estimation. To make estimation precise many works have been carried out by considering a lot of constraints. In this paper, facial age estimation is done more accurately. SFTA method is used for feature extraction and meticulous results are obtained for all age groups. Histogram equalization is done using the Otsu algorithm and three layered Deep Neural Network is used to classify the age group. In a Deep neural network, softmax normalization is done in the final layer to preserve the outlier values. By extracting 45 feature values concerning color and gradient, key point descriptor, orientation, shape and texture better estimation are obtained.

Keywords: *Face Recognition; Image Edge Detection; Image Segmentation; Pattern Recognition; Texture Analysis.*

1. Introduction

Facial analysis and face recognition are widely used in many machine interactive applications. Face as indexing the attributes of a person is vitally used in the field of image processing, computer vision and human computer interactions. From a facial image or video stream many statistics such as age, gender, ethnicity, texture, etc. of a person can be retrieved. After obtaining all this information from a face, the detection of an eye is very cardinal. The eye detection is hindered by illumination, pose and expressions. This algorithm concentrates on face detection and feature extraction. The face is detected using viola-Jones algorithm and features are extracted using SFTA method. The age estimation in facial images is an exacting job in providing a highly accurate result. To make estimation precise many works [1], [2] have been carried out by considering a lot of constraints. The research has succeeded in many ways by concentrating in a particular stream and by compromising many other criteria. Using this paper, multiple features are focused and better results are obtained in overall age estimation. The algorithm is fine tuned as when the training and testing are done significantly. The training set is increased and the accuracy is achieved. The testing is also done on celebrity images to check the performance of the algorithm. Most of the limitations occur in the images which consist of images with various expressions [3]. When the facial features are appropriately extracted devoid of the expressions, the estimation accuracy can be improved. Since the features are extracted by considering the fractals, this limitation has been rectified. The images are also collected such that poses of all the images are not unique, the expressions are different as well as the images with makeup effect and images without makeup effect are also considered. This boosts the training set and which is depicted as accuracy improvement in the testing tests also.

2. Related works

Face aging has attracted many researchers [4] in analyzing facial age, many areas such as psychology, cosmetology, human computer interactions, computer visions, criminology, etc. Paper [5] uses SIFT based features and MLBP based features to identify face matching in images irrespective of age. The multi-feature discriminate analysis (MFDA) is used to process both the features in a unified network. The face matching is achieved by multiple LDA based classifiers. Paper [6] estimates age using ANFIS method which utilizes LBP and HOG features. In paper [7] geometric features are considered using PCA method. Paper [8] uses AGES (Aging pattern subspace algorithm) method to estimate age. Paper [9] uses artificial neural network for classification. It classifies age first into four groups childhood, young, youth and old and then divides into two groups in each category. In all these papers age estimation is studied on particular data set and have analyzed age in specific age groups. SIFT [8] algorithm applies a four stage filtering approach. This stage of filtering attempts to identify those locations and scales that are identified from different views of the same object. SIFT key point of the object are first extracted from a set of reference image and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image with that of the one which is stored in the database. Identifying the matches, the age of the person is retrieved. The SIFT method provides robust and fast estimation on both 2D and 3D images but accuracy is less. In this algorithm, the number of images and the number of age groups is increased to achieve better accuracy. This algorithm uses SFTA method to retrieve features and classification is done using DNN. Using SFTA 2D image is alone concentrated and the accuracy obtained is higher.

3. Proposed method

3.1. Features

To perform staunch recognition [9], [10] in an image it should be possible to extract the features from the image even after preprocessing the image by changing the illumination, scale and orientation. In this paper five major features are considered for classifying the age group. They are orientation, texture, key point descriptor, shape, color and gradient. Based on these five major features 45 feature values are retrieved. To perform feature extraction it is required to accomplish segmentation and filtering of the image. This eases labeling and independent processing of the image. Prior to extraction, the image is normalized using Otsu algorithm. The image is converted to fractals and the feature values are extracted. The following are the five major features used for classification.

3.1.1. Orientation

When orientation is analyzed, the aspects of edge, the certitude of flexure and corner details are availed. Concerning the properties of the input image, the axis for the fiducial points is assigned. For instance, when both eyes do not incline in a straight horizontal line, the image is aligned to regularize the face. The approach taken to find orientation is

a) The smoothened image (I) is selected using key point scale.
b) The gradient magnitude (M) is computed by,

M (x, y) =

$$\sqrt{(\mathrm{I}(\mathrm{x}+1,\mathrm{y}+1)-\mathrm{I}(\mathrm{x}-1,\mathrm{y})^2+(\mathrm{I}(\mathrm{x},\mathrm{y}1)-\mathrm{I}(\mathrm{x},\mathrm{y}-1))^2} \quad (1)$$

c) Orientation histogram B is computed from gradient orientations of the sample point
d) The highest peak in the histogram is located.
e) Multiple orientations are also assumed for some points.

3.1.2. Texture

Image texture analysis is wielded in segmentation and classification. It gives the details of the spatial arrangement of color or intensities in an image. For more refined segmentation, the average gray level and spatial frequency provide precise details. Structured approach and statistical approach provide clear ways to analyze the structure details. The texture details can be learnt by image edge detection. The edge points and the direction of the edge points ease the study of texture.

3.1.3. Key point descriptor

The key point is a circular image region with an orientation. It is described by a geometric frame of 4 parameters. Key point coordinator x and y plot scale (radius of region) and its orientation (angle). From the numeric description of the key point, it is found that the there is no dependency between the description and the position of the point. From different positions, the descriptor remains same irrespective of the position. This happens due to the translation of the image. The image transformation is inevitable in image processing.

3.1.4. Shape

The shape features must have certain properties. From the shape, it should be able to identify the categorization of age. The extracted feature should not be affected by scaling or any translation operations. Even after preprocessing, from the shape feature, it should be possible to identify the age. Efficient shape features must be afffine invariable. The linear mapping from the coordinate system should preserve straightness and parallelism of lines. The extracted feature should not vary with affine transforms. The strength of noise should not be affected by the shape feature. In case some regions of a shape are occulted by other, the feature of the remaining part must not change compared to the original shape. The feature should be statistically independent which means the representation should be statistically independent. The feature should also be reliable. The feature must remain the same.

3.1.5. Color and gradient

The color and gradient of the image should provide precise or distinct information. The information should be repeatable and accurate with photometric and geometric variations. The efficient feature should be substantially significant and robust in identifying the age group. The color feature is used to discriminate the fractals easily. As we concentrate on color images [11], the intensity variation delineates intensity variation and thereby eases estimation. The gradient provides the directional change in the intensity of the image. The color and gradient have an impact on the texture of the image. This induces difference in age by providing smoothening effects. So concentrating both color value and texture value the aging effect can be understood.

3.2. Steps

The input image is retrieved and then the image is normalized by using histogram equalization to obtain a standard image. The color image is converted to HSI image to devoid contrast effect in the image. The image is aligned for size and orientations. From the processed image, the features are extracted. The feature details are stored in the database. In the training phase of the project, 1000 images have been collected and the training of images is done. When an input image is given, the image is preprocessed and the feature details are extracted after segmenting the image to obtain the fractals. The extracted values are compared with the feature data stored in the database. After this pattern recognition, the age class of the input image is displayed. The algorithm used is SFTA for feature extraction and DNN for classification.

3.2.1. Training phase

Obtained input image if retrieved as a color image, it is converted to a grayscale image. This conversion is done to obtain fine edge details. Otsu method is used for processing. The histogram equalization is done to obtain the threshold values. The matrix of threshold values is obtained. The threshold values in gray scale are converted to black and white to avail outline details leaving the intermediate content. The identification $O_{(x,y,\sigma)}$ is done by using a Gaussian function to the input image.

$$\mathrm{O}_{(\mathrm{x},\mathrm{y},\sigma)} = \mathrm{L1}_{(\mathrm{x},\mathrm{y},\sigma)} - \mathrm{L2}_{(\mathrm{x},\mathrm{y},\sigma)} \quad (2)$$

Where $O_{(x,y,\sigma)}$ is the difference between the same input images which are applied to two different Gaussian functions. L1 and L2 are input images which are applied Gaussian functions.

$$\mathrm{L}_{(\mathrm{x},\mathrm{y},\sigma)} = \mathrm{G}_{(\mathrm{x},\mathrm{y},\sigma)} * \mathrm{I}_{(\mathrm{x},\mathrm{y})} \quad (3)$$

Where G(x,y,σ) is the Gaussian function where the scale is changed for L1 and L2. $I_{(x,y)}$ is the input image. * is the convolution operator. Only by segmentation, the intensity values in different regions are analyzed. By thresholding, the region of interest can be extracted from the background region. Clustering based thresholding is done by using OTSU method. The image is divided into a finite number of groups and each of the group is assigned an index value. These indexes are stored in a finite location. As an input image is given, a set of threshold is returned. Using multilevel Otsu algorithm, the gray level value and neighboring pixel's average are calculated. Using this algorithm the threshold which minimizes the class variance of the input image is found. Recursive application of the algorithm to each image region aids in finding the total threshold. All the arrays which are the various groups obtained by thresholding are then combined to obtain a single column to ease histogram equalization.

$$\text{sigma\_b\_squared} = \frac{(\text{mu\_t} * \text{omega} - \text{mu})^2}{(\text{omega} \times (\text{l} - \text{omega}))} \quad (4)$$

This yields better results in digitization of all images. The results are better even in the case of noisy images. The extracted features are stored in training dataset and are used for training the dataset. From the binary image, the borders are retrieved. The border details are obtained using the function HausDim (I) which returns the details of the border of the image I. The fractal dimensions are obtained using this function. Using this descriptor value, the age is estimated. The function returns the fractal dimension D of an object represented by the binary image I. Nonzero pixels belong to an object and 0 pixels constitute the background. The 45 fractal values obtained for each pixel position are stored in the database file for both X and Y axis.

3.2.2. Testing phase

In the testing phase, when an input image is given, the image is normalized. Histogram equalization method and SFTA are applied to the input image. The features are extracted and the extracted features are compared with the results stored in the database. The Deep Neural Network is used for classification. Three layered neural network is used. This is done to improve the reliability and increase the robustness. In the first layer, an XOR operation is applied to the extracted features. The second layer is used to store the class labels which provide the age category. The third layer stores the details of the X and Y coordinate values which are the threshold values extracted at various points. The neural network feed forward pass is performed using the function

nn= nnff (nn, x, y) (4)

Where nn, the neural network value is obtained by using the function

nn=nnsetup ([size (Train_X, 2) 5006]) (5)

Where Train_X is the training image and x and y are the coordinate values. From the obtained neural network structure, the updated layer activations, error and loss (nn.a, nn.e and nn.L) are calculated. The prediction algorithm matches the values of the given input image with the values stored in the database. The nearest match value is found and the result is obtained. The result is obtained as class labels. Since only three layers are used in the neural network, the result is accurate and also the elapse time is very minimal. In the third layer softmax normalization is used. So we obtain the impact of outlier values also. This is important because each fiducial point possesses impact on aging. When considering celebrity images, the identification of age is very arduous. But in this algorithm better recognition of age in celebrity images is found.

3.3. Neutralizing makeup effect in age estimation

On digital calculation, it becomes easy in identifying the edges and the age is also easily identified. On seeing the images in Fig.1, the age estimation is very difficult for the human eye. Due to make-up effect, the age seems to be very less as of the actual age. This is due to the fact that the wrinkles are hidden by make-up. But when the image is converted to grayscale and SFTA is applied, edge details are analyzed and the variation in the extracted 45 feature values is noted. The far variation in key point descriptors and texture value can be studied. These values are compared to the stored training set database values and the age is predicted. Consideration of makeup effect [8], [12] seems to be a serious challenge in estimating the age. Using this algorithm, the estimation of age in the images of celebrities with makeup effect is done. But the estimation is found to be same as that of the original age. This is because human perception considers the facial makeup, hairstyle, physic and also behavior. So it is found to be difficult to estimate the age of a person in case of makeup effects. But on digitization, the facial age estimation algorithm concentrates on the face part alone. So the algorithm has proved to achieve better results. The various challenges such as illumination, pose, expression, plastic surgery the effect of cosmetics makes the facial recognition systems abominable. These cosmetics cause the change in size of the face, eyes, nose, mouth, change in texture, elimination of wrinkle effect, minimization of eye corner effects and eye darkening effects. Since age estimation is reliable on these features, difficulties occur in estimating the age [13]. The makeup effect and aging differs from person to person. The following are the examples of the makeup effect. The image of a person at age 30 and age 62 shows less virtual change as in Figure 1. Aging is very minimal and human estimation of age is also very tedious due to the makeup effect. But the aging can be studied by keen observation of the faces. The lobes have become longer and the forehead has become broader. Thinning along the hairline is also noted. The age cannot be mentioned exactly on seeing the image. This age estimation system, classifies the age with age labels 30-34 and 60-64 respectively.

Fig. 1: Aging More Effective in Eye Regions

The image of the same person at age 25 and 65 in Figure 2, shows the signs of aging in the lower part of the face.

Fig. 2: Aging More Effective in Cheeks.

The face has thinned and wrinkle effect is very well visible in cheeks, chin and neck region. The eye region also very well explains the effect of aging. Using this algorithm the age is labeled as 25-29 and 65-69 respectively. By analyzing all these images, it is inferred that makeup effect reduces the age in appearance. The presence of makeup is denoted as an increase in the intensity in those particular regions. When this intensity is higher around the eye and mouth regions, the age is easily identified along with the other features. The skin tone is uneven in the images with makeup effect. By combining this uneven tone of skin and the other age properties, the estimation of the age is done.

4. Results

Using this algorithm, 45 features are extracted from the input image. The size of the feature vector is considered as 8 and 45 features are extracted from all the images (I). This is the achieved using the function sfta (I, 8) and (6 × (size of the vectors) - 3) vectors are received. The size of the vector is assumed to be 8 to consider 8 directions in the image. The features are returned as vectors. In the training phase, all the 45 features of each training image are stored in the database. When an input image is given, the features are extracted and the features are compared with the feature values stored in the database. With the results obtained after the comparison, the age group to which the input image matches is given as the estimated age group. The facial images are normalized and the feature values are extracted. The drawbacks of photometric and geometric variations are ignored. In case of celebrity images, it is very hard to predict the actual age. This occurs due to their lifestyle, makeup effect, dressings and mannerism. Using this algorithm, it is found that the age estimation in facial image can reveal the actual age. In spite of makeup effects, it is found that the estimated age is almost similar to the actual age. This estimation is achieved based on the obtained feature values. 45 feature values are extracted based on various attributes such as color and gradient, key point descriptor, orientation, shape and texture. These values are extracted from any input image.

As in Figure 3 and Figure 4, the image of the same person in two different ages is compared. Both the image is captured with makeup effect. The estimated age of both the images is different. The feature values are extracted for both the images and all the 45 feature values are plotted against the fiducial points considered for each feature. The graphs are plotted in the color and gradient values, key point descriptor values, orientation, shape and texture. These graphs explain the results of comparison between both the images. From the graphs it is very lucid that the age estimation can be done in an accurate manner in case of makeup effects. The age estimation is done on the input image and it is devoid of illumination, pose and size of the image. The muddling effects in more digital processing are rectified using this algorithm. Though the image of the person in both the figures are of different pose and illumination, by analyzing the feature values of color and gradient, key point descriptors, orientation, shape and texture, the age group is estimated to be 20-24 in Figure 3 and 40-44 in Figure 4. In both the figures 5 fiducial points are obtained from forehead region, left side and right side of the cheeks, tip of nose and chin region. The color and gradient values in these points are extracted. The color and gradient value in both images shows dramatic variance indicating the difference in the age of the two images. The variation in this graph is the increase in the age of the person. The key point descriptor values of both the images show little variation in the middle portion of the graph. Since various regions in the face possess different values, 15 key points are extracted. From the 15 fiducial values obtained for the key point descriptor, the graph is plotted. Among the 15 values 10 values are more different which highlights the increase in age. The key points are the same person but still there is variation indicating the difference in age. When comparing the orientation values of both the images, there is very little variation. 10 fiducial points are obtained for orientation. For obtaining 10 values, the face region is divided three horizontal rows. From the first row, which is the top most row, 3 values are and from the bottom row, which is the third row, 3 values are extracted. The top three values will reveal the eye corner values and the forehead region values. The bottom 3 values depict both the lip corner and chin values where all aging signs are noted. From the middle row, 4 values are obtained. The values correspond to the cheek points on either side of the face and both the corner values of the nose. This is to find the actual variable shown in the orientation of the image. The two curves show a little difference in orientation as the face region alone is cropped from the input image. Considering the shape difference in both the images, 5 fiducial points are extracted. The difference in shape of the two images is also very little. So the estimation based on the shape alone cannot provide accurate age. Here all the aspects are take into consideration to provide a foolproof estimate. Comparing the texture difference in both the images, 10 fiducial points are taken into consideration. The vital difference is observed in the texture values. Though the makeup effect is present in the image, the texture values are found to be different. The texture in human perceptions would seem to be young. But extracted texture values are different, depicting actual age.

In Table 1, the experiment is also done on next category of images where the images of two different persons belonging to same age are tested. On testing some images of different subjects belonging to the same age, it is found that the age estimation is done in an accurate manner. On testing 200 celebrity images, the age is estimated accurately. On appearance, the images in each row of the Table I look to be of persons belonging to different age group. But the actual age of both the persons are same. The feature values when analyzed, the values are found to be of nearly same values. The actual age and the estimated age are same. In Table 1, the images in the set A look younger compared to the images in set B. This inference are normal human assumption. But the fact is that the images in set A and the images in set B are of equal age. This is the way people age differently.

The aging varies from person to person by their heredity, makeup up, habitat and other factors. But in keen observance of the eye corners, cheeks and forehead, the age can be studied easily. This algorithm analyzes the feature values in various aspects such as texture, size, orientation and so the values seem to be of nearly equal values. In the first row of the table, the appearance seems different, but the key point values are almost equal. So the age is estimated to be of the same age. In row 2 of the table3, the age of the person in set B seems elderly due to the presence of gray hair and baldness of hair. The image in set A seems young due to the absence of gray hair. But in the analysis of the facial features, the hair portion is not much concentrated. The feature values that are extracted are almost equal valued. The texture value, key point descriptor values provide fine details of the age. So the estimated age is same as of the actual age. In row 3 of table1, the person on set A looks younger in appearance compared to the one in set B but the feature values are nearly equal. In row 4 of the table 3, again the image in a set A look younger than in set B, but the estimated age is same as that of the actual age. The image in set A has less facial hair, so the values that are extracted provide a clear description of the texture and shape. In the image in set B, the presence of facial hair is more. The shape values and key point descriptors are extracted easily. The texture values and color and gradient value of both the images are different, but the estimated age is same. This is achieved because the shape, orientation and key point descriptors are equally concentrated.

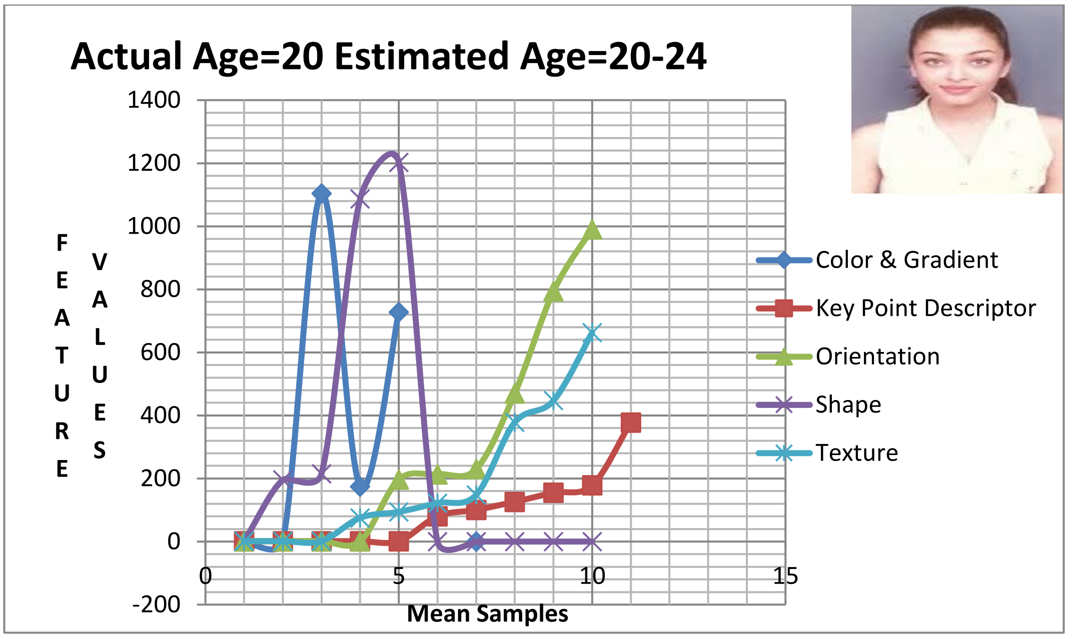


Fig. 3: Plotted Feature Values of Image in the Age of 20.

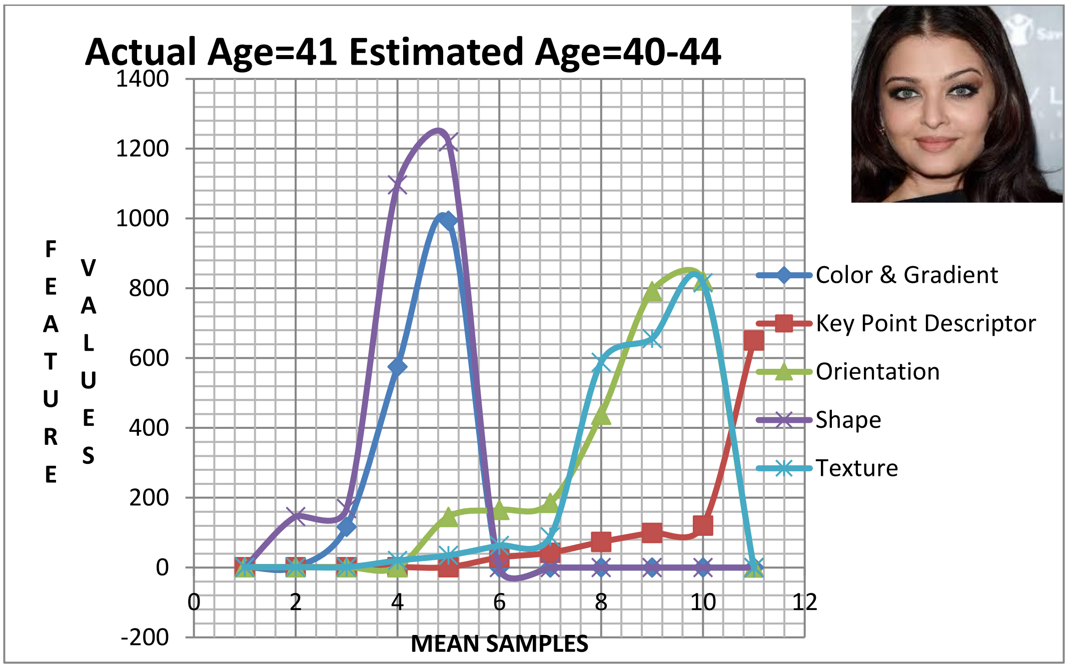


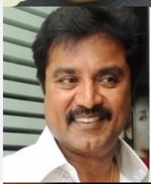
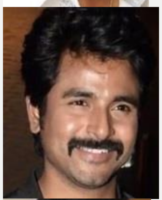
Fig. 4: Plotted Feature Values of Image in the Age of 41.

Considering the two images in Figure 5 and Figure 6, the comparison graphs for color and gradient value, key point descriptor value, orientation value, shape and texture values are studied. The feature values are extracted from both the images and are plotted to find how far they are related. The graph is found to be of similar size for both the images. This is because the extracted feature values seem to be almost same for both the images. The color and gradient, orientation and texture are almost similar in both the images. This similar value brings them under same age group. The key point descriptor and shape values are a little different. The texture seems to be almost similar for each age group. It is studied that the color and gradient value, the texture, the orientations in the image have an impact in the age which is noticed in digital only. The assumption of age made by human vision is by considering the external factors such as makeup, shape, dressings and behavior.

The images below this age group and above this age group are found to have nearly similar values for the shape feature. The orientation shows the difference in aging in the eye, corners, lip corners, edge of nose ends, forehead region and edges of the chin. So these 10 fiducial points are considered to make the note of aging. In Figure 5 and Figure 6, the orientation values are found to be nearly equal. So the estimated age belongs to the same age group. The key point descriptor values of both the images are different which are noticed from the plotted graphs. The key point descriptor values of both the images are little different exhibiting the variance is the facial features. The normal shape of a face image change with respect to age. This occurs in most of the people. Persons belonging to same age, possess similar shape on average. This varies with various conditions such as obesity, lifestyle, genetic reasons and so on. This high difference in shape is noticed in the age groups from 20 to 60. The color of each image is different. When the color and gradient are considered, the change in gradient with respect to color signifies the difference in the age. By combining all the 45 feature values, the average age group is predictable.

This better estimation is achieved in facial images. The classification is based on a deep neural network, which is three layered. The neural network identifies the exact age by manipulating all the feature values which are extracted. The classification is done only after matching all the three layers. In matching the layers, the use of the softmax normalization method includes the mean value as well as the outer value.

Table 1: Age Estimation within Same Age Group

S. No	Image set A	Image Set B	Actual Age	Estimated image
1			36	35-39
2			62	60-64
3			32	30-34
4			42	40-44

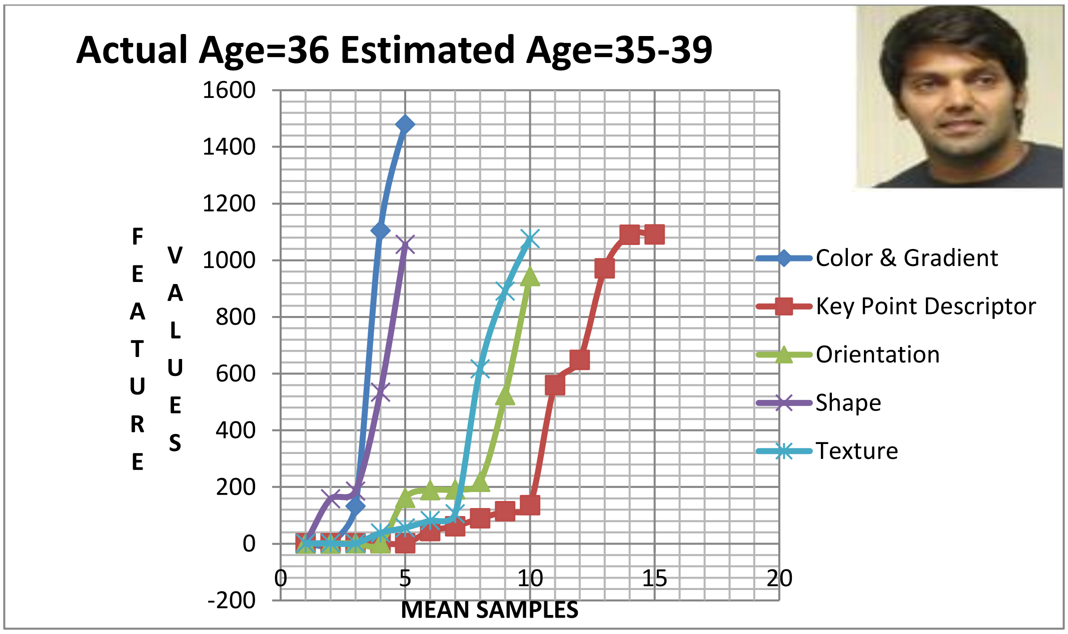


Fig. 5: Plotted Feature Values of the Image in Set A.

The gradient log normalization considers the mean value obtained from the input values and also the outer values which hold the values of texture. The texture differences hold the aging factors and which, when excluded may make the age unnoticed. So the softmax normalization aids in the inclusion of each data value in précising the estimation of age. Every individual feature value and the values stored in the database are concentrated. By comparing all the results, the refined age is obtained. Hence this algorithm concentrates on the difficulties confronted in the previous re-searches [13-19] such as makeup effect, different aging, slow aging, expressions, and the presence of facial hair and so on. This amelioration in this algorithm is achieved using SFTA and deep neural network [20]. If the features are extracted using some other techniques like SIFT method, the scaling effects will be excluded and the feature values can be obtained but the determination of expressions cannot be obtained. The inclusion of the fractals in extracting the features provides retrieval of values which consists of the texture details, the most vital source of age determination.

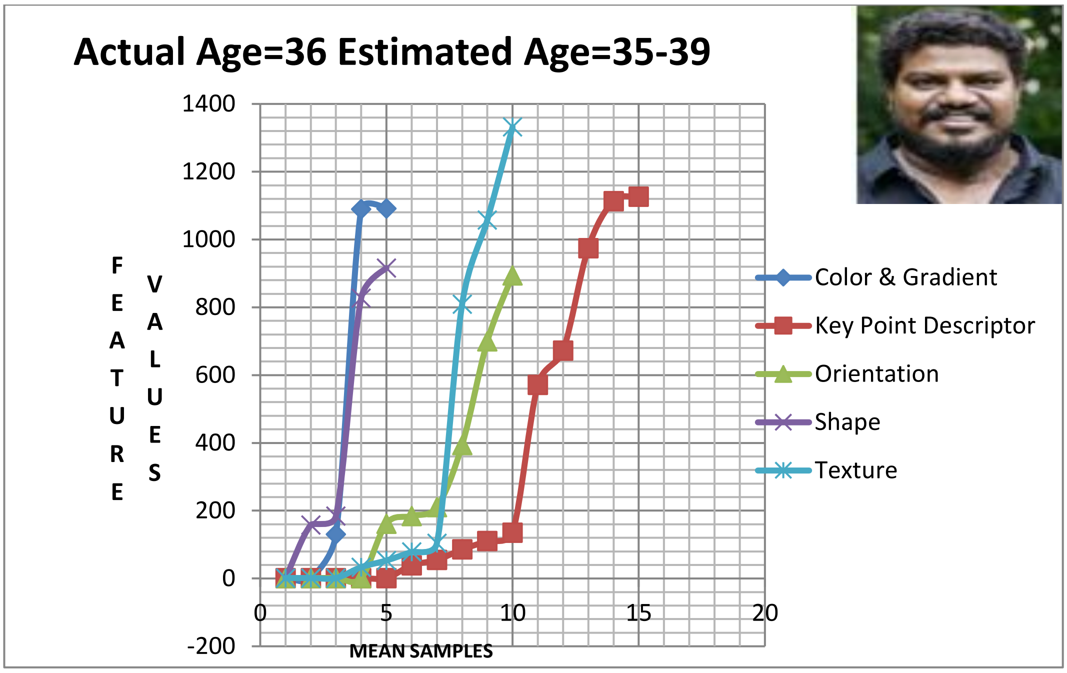


Fig. 6: Plotted Feature Values of the Image in Set B.

The fractals are stored in the database and the features of the input image is extracted and compared with the training set values. When an appropriate matching is found, the age group is classified. The images are segmented to obtain the details and so the fractal values are also very precise. The sample values when plotted against the respective mean values provide the exact age of a person irrespective of makeup, pose and illumination.

Many authors have proposed several successful algorithms for age estimation, but the estimation of age is deviated due to the unconstrained face image. This algorithm works on the images from the databases such as FERNET, MORPH and internet images. Since more number of images train with faces belonging to different nations and communities, the estimation obtained is comparatively better. The inclusion of male faces and female faces in the database also has a vital impact in prediction of age. The presence of facial hair and rough texture in male faces and smooth texture without facial hair in female faces result in the different categories of age. This problem is rectified by including both male and female images in nearly equal proportion in the database. The classification is also not only based on the texture but also the shape and values obtained in the fiducial points.

Fig. 7: Different Facial Expressions with Diffrences in Texture of the Image.

As in Figure 7, the effect of facial expressions has an impact on the estimation of age. This deviation happens due to the reason that the texture becomes smooth in the cheek regions with happy expressions and wrinkles appear near the lip corners. The wrinkle effect can be noticed in case of anxiety expressions also. The expression of anger in the face shows reduced width of the face as compared to happy expressions. Thus the impact of expressions is rectified by the training set data. The images of same person in different age as well as different expressions are also stored. The classification when done with the comparative results of texture, shape, feature values, the resultant value obtained is accurate. Thus it is inferred that there is an improvement in the estimation of age.

5. Conclusion

The age estimation is done on images of the same person in a different age and estimation of age in different persons belonging to different age group. By comparing the results obtained with the actual age, high accuracy is obtained in estimating the ages of the person. The experimentation is done on images with varying lighting conditions and the results have been found to be accurate. This is achieved using the normalization of the image. The implementation is carried out using MATLAB. Using SFTA feature extraction algorithm, 45 features have been generated and stored in the database. The features are extracted with respect to the different parameters such as orientation, texture, key point descriptor, shape and color and gradient values. Hence the net result obtained is higher. The drawback and flaws incurred in considering either shape or texture are regulated by concentrating both the parameters. The neural network feed forward passes allows the categorization of using the normalization technique appropriate to the values extracted. By normalizing, the ignorance of eminent values having a prominent impact on the estimation of age is avoided. The DNN classification with three layers provides better accuracy and also the speed is increased. The classification is based on the extracted feature values as well as the label on the training set. The comparison is done to arrive at the estimated age. Since the estimation is done under different criteria, the result which is obtained is found to be an accurate age. The drawbacks of phase variation, illumination and size of the image are all rectified. The number of age brackets is increased to narrow the width of the age group. The furtherance is achieved with the inclusion of all these factors.

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