Advances and Applications in Mathematical Sciences
Volume 20, Issue 7, May 2021, Pages 1297-1304

QUINTESSENTIAL FEATURES UTILIZED FOR GESTATIONAL AGE ASSESSMENT THROUGH DEMEANOR OF HUMAN FACIAL IMAGES

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Abstract

The age is identified with the semblance of the features obtained from the face image of a person with the features stored in the database. The fiducial features which are extracted from the person's facial image is compared with the values which are pre-stored in the database of the feature values of the facial images. The age is classified as eight groups based on the shape and angular measurement values. The extraction of feature is achieved by Segmentation based Fractal texture Analysis algorithm (SFTA). The measures of the features are done with the aid of angular measurement method. The classification of the age is obtained in the age groups categorized into seven. The first group encloses age between 1 and 10, the second group between age 11 and 15, the third group with age between 16 and 25, the fourth age group between 26 and 35, the fifth age group between 36 and 45, the sixth age group between 45 and 60 and an elderly age group from 60 years and above.

1. Introduction

All The current era is the digital era with a remarkable growth in soft technologies and computing. The world has drawn its attention to the advantages of digital processing and data handling. The marvelous progress in the availability of the databases in image and video format has created a necessity in the field of automation.

2010 Mathematics Subject Classification: 44A05, 44A10.

Keywords: facial image, SFTA (Segmentation based Fractal exture Analysis), angular measurement, features, classification.

Received September 7, 2020; Accepted February 18, 2021

The proposed system concentrates on processing the facial image, extracting the features from the input image to classify the age group of the input image. The process of identification of the features from the face consists of two major stages such as extracting the features and classifying the face into the required category. Extraction of features and establishment of classifiers are the major considerations in the process of facial image processing and estimation of the age from the classified results. The age estimation from visage expects the identification of the eyes from the face first and then various measures are identified from the facial image. The features are those with respect to shape of the face and the texture of the face. This paper discusses the various aspects in shape of the face and the methodologies used in finding out the age.

2. Proposed Method

The appearance of the human face encounters different variations with the progress of aging. The major certitude in this deed is that estimation cannot be provided with certainty by the human. The fact is there are several hurdles in judging the age even by human. In this deed there is a need for an automated system which can provide an age fact which defines a specific age category based on the extracted features (Ahonen Hadid and Pietikainen, [1]). The objective of the research is to normalize the input face image and to extract the required features from the normalized face image. With the retrieved features, the age group of the subject is categorized. In extracting the features, the details of eye portion were determined, the fiducial points were located and the measures of face were also determined with respect to the geometric ratios. The SFTA method was used to extract the fractal features and major information regarding the feature values was obtained. The features were extracted in terms of color and gradient, descriptors of the key points, orientation, shape and texture. With this regard a total of 45 features which included 10 values for orientation, 10 values for texture, 15 values for key point descriptor, 5 values for shape and 5 for color and gradient were extracted. With these fractal values, local features such as the geometric measures of forehead, nose region, mouth region, height and width of face were also considered. The facial angle with respect to the angle developed between the eye points and the lip midpoint was taken. The angle value provided the range of age. This range and the fiducial value ratio were compared and a final age group was identified. All the feature values and geometric measures were used to train the system. With proper training, the age was estimated for the testing image. The otsu algorithm was used for performing normalization and the classification was done using deep neural network. In a Deep Neural Network (DNN) (B. Ni, Z. Song and S. Yan, [2]) softmax normalization is performed. This normalization is done to retain the values which lie in the edge area. The categorization of the age is done under five age groups which are the first group enclosing age between 1 and 10, the second group between age 11 and 15, the third group with age between 16 and 25, the fourth age group between 6 and 40 and an elderly age group from 40 years and above 0 to 10 years, 11 to 15 years, 16 to 25 years, 25 to 35 years, 35 to 45 years, 46 to 60 years and above 60 years. The accuracy rate is achieved at a higher rate with the inclusion of both fractal features and biometric features. Hence an ideal model has been proposed to retrieve a facial image, preprocess it and identify an approximate age group. In the proposed method, the estimation of the age is done through the steps as shown in the Fig.1. The image is obtained through any source. The only requirement is that the image is a two dimensional image. The input image is normalized and from the normalized image, the feature extraction id done. The method used for the extraction process is Segmentation based Fractal Texture Analysis method. The features are retrieved and the values are based on the position of the facial features. The major role is the prediction of the position of the eyes. When the eye position is found, the other facial features can be obtained through the face measures. The angular measurement technique is used to estimate the positions of the facial features.

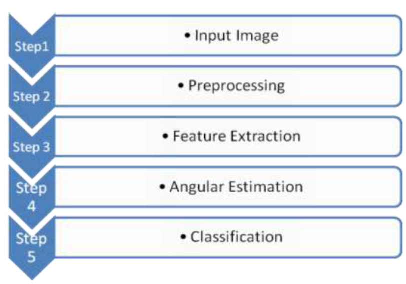

Figure 1. Steps used for Estimation of Age.

As in Figure 2, the images show differences in the shape of the face which is also with respect to the progression of age. The estimation of the age is achieved with the value of the angle which is calculated from the obtained features of the face. The features extracted from the SFTA (Chen and Hsu, [3]) algorithm provide the positional value of the facial features and the angular calculation of the facial features provide the values which are categorized for the estimation of the age of the person. The texture value and the shape value provide the defined age value of the person. The shapes of the face are in different forms. The different shapes are in the forms oval, long, round, square, heart and diamond. The age estimation is analyzed in different forms of the faces. The analysis of the estimated age is performed to ensure the accuracy of the algorithm. The results have shown that the accuracy is achieved in all different shapes of the faces.

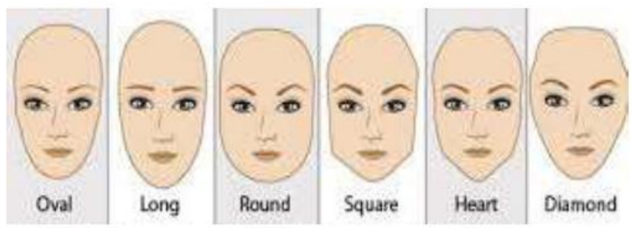

Figure 2. Different shapes of Face.

On analyzing the facial properties, there are different shapes of the person. The different shapes provide variations in appearance but the estimation of the age from the face has shown less violation in the accuracy of the age. There are different shapes of face in appearance. The different shapes are oval shape, long shape, round shape, square shape, heart shape and diamond shape. Deep Neural Network is used for classification. This has multiple set of functions as compared to the shallow networks hence is mostly used. The deep neural network provides various functionalities like applying layering using pools for every feature. The vector values provided as input were connected to the entire neural network. The forward and backward propagation is possible to obtain the right age of every layer. As the duration of calculation was lengthy for calculating the entire gradient model, images were processed in batches with each age group trained separately. The performance of deep neural networks is made more accurate with the aid of four layered DNN (Dong Y, Liu and Lian , [5]). The image database is also improved in size with images of around 1000. The images which are used are labeled images. The extracted features were stored in the database. The Deep Neural Network was used for classification. Deep neural network has a layering of four to obtain enhanced reliability and a shoot up in the robustness of the algorithm. In deep neural network the first layer does the aggregation of the pixels in order to recognize the edges of the image and the second layer groups these detected edges. In the first layer, matching of the angular value and the extracted feature value with the broad category of age group was done. In the second layer, digital operation XOR is performed on the extracted features. The third layer stores the details of labeling the classes with the feature of the particular category. The fourth layer stores the coordinate position values with respect to X and Y positions which are the values of threshold obtained in different position values. The function used to calculate the pass in the feed forward neural network is given by the Equation (1).

$$nn = nnff(nn, x, y). \tag{1}$$

The output was obtained in the form of a network structure which consisted of the updated activation layer, the error and the loss. In training the system, the functions associated were either of the direct training which used only limited training set data or of the training of the entire network. The neural network was obtained with the formula given by Equation (2)

$$nn = nnsetup([size\ (Train\ X)5006]). \tag{2}$$

Here Train is the training image and the coordinate position is in terms of the values of x and y. Classification of image provided an output which was likely to be in the predicted category based on the matching criteria with the data taken from the training set. Deep Neural Networking (Li and Yang, [6]) is a process where the principal of working is as that of a human brain. The deep neural networks are interconnected to achieve a refined output based on machine learning. This provided better results as compared to Guo and Huang [8]. In PCA, the grouping of related and nonrelated terms were considered. In this algorithm four layers were used. The nearest match value was found and the result was obtained as class labels. As a result of using four layers in DNN, time taken is reduced and the accuracy is increased. In the fourth layer, as always softmax normalization (Guo and Mu, [8]) was used in the last layer of the neural network. Softmax normalization normalized the input vector value into a probability distribution in the range which was proportional to the input value in terms of exponentiation. So the major variation in the input values were normalized to obtain an equal range of values and also the impact of outliers was obtained. This is important because each fiducial point (Guo and Fu [8]) possesses impact on aging. The softmax classifier was used to generate single output from multiple classes. The output generated from softmax classifier is an intuitive output which was normalized by identifying the class probabilities. The classified output is a normalized class probability which is given by Equation (3).

$$sf(xi,\ weightage) = weightagexsf(x,\ weightage). \tag{3}$$

The above equation makes the $sf(xi,\ weightage)$ to be equal to weightage of xi. To find the entropy of loss, the Equation (4) is used.

$$Li = -sfyi + \log \sum jesfjLi = -\log \left(esfyi \sum jesfj\right) \tag{4}$$

The variable $f_j f_j$ denotes the element j of the score of vector class ff. The total loss of the dataset is obtained from the mean of $LiLi$. Multilayer Relative Propagation methodology was used to obtain a single output based on decision making from the various existing classes. The resultant value was obtained from the MRP (Multi-layer Relative Propagation) [10] function which is given in Equation (5)

$$MRP(i) = P(cRF), \tag{5}$$

where P is the probability function, c is the component and Rf is the Relevance function. The Rf denotes the contribution of the several layers in obtaining the final decision. This decision was based on the probable value. The relevance function was obtained from the probability score obtained from the input and the hidden layers. The probability score was obtained when the MRP function was equal to the probability of the particular component in each layer.

3. Results

In these classes, the probability of relativity of the class was obtained. From the matching value, the estimation is done. The estimation is done based on the relativity of the values with the database values which are classified into five age groups. the obtained result is explained in the Figure 3. The relativity shows the matching rate of the age from the facial images. The various shapes of the faces are considered. 20 images are taken from each shape of the face and they are analyzed to obtain the age of the person from the input image.

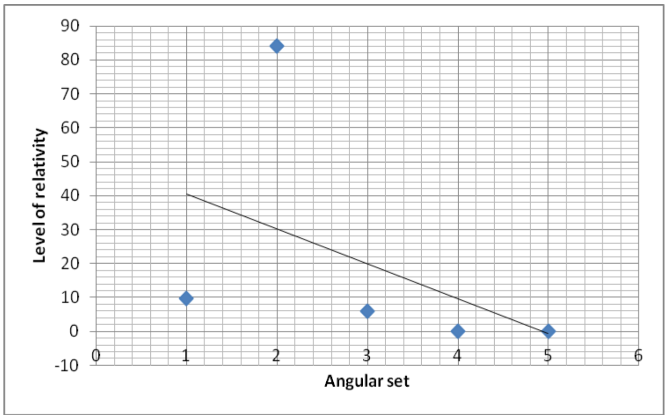

Figure 3. Angular Estimation Result.

4. Conclusion

Thus this paper discusses the factors involved in the assessment of age from visage. The estimation of age is done based on the shape and texture factors. The various shapes of face is analyzed and the age is estimated based on the feature values which are extracted. The matching of the extracted values with the stored database value is used for classifying the age. The result has rendered the inference that the shape values have a high impact on the estimation of the age. There are various areas where the estimation process is used in this digital era. Hence this research can enhance the focus in face detection, recognition of a person, getting bio-information of the person and also in various human computer interfacing applications.

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