

## Measuring the Craniofacial Growth for Determination of Human Age through Classifiers

Sreejit Panicker<sup>1</sup>, Smita Selot<sup>2</sup> and Manisha Sharma<sup>3</sup>

Submitted in Oct, 2015; Accepted in July, 2016

**Abstract** – An individual face reveals an array of information that can be age, gender or identity. The features play an important task in the estimation of age for a given person, just by looking at the face. In this research, the work is to design a model which classifies age with respect to features taken out from individual facial images by means of Neural Network (NN). In recent years, Artificial Neural Network (ANN) has been extensively used as a means for solving many decision making problems. In this paper for classifying age group a feed forward propagation neural networks is constructed from gray-scale facial images. Age groups are classified in four groups, including babies, young, middle-aged, and adults, applicable in the classification method. The course of action of the system is partitioned into three segments: locality, feature extraction, and age classification. The global features used to distinguish child from middle aged and adults is based on the ratios computed using the eyes, nose, mouth, chin, virtual-top of the head and the sides of the face as those features.

**Index Terms** – Age determination, Facial Feature parameter, Neural Networks.

### 1.0 INTRODUCTION

Aging and determining the age of human through facial parameters using various approaches in the area of computer vision and pattern recognition have gained considerable importance in recent times. With the advancement in technology, age determination is need for various real world applications. Aging is a natural phenomenon which exhibits the changes, more evident in context to facial growth.

Global features are considered by many researchers in varied areas such as identification, classifying gender, expressions and so on. Considering Age estimation and classification with facial features there is scope of further improvement. Researchers have worked for age estimation which give results for ages, or classify the ages in categories such as child, middle aged and old using extracted features.

An appropriate approach for age estimation to classify age in specific range is still a demanding problem. Thus, we focus the

study on more specific extraction of facial features using statistical methods.

To achieve our goal, we create a database with extracted characteristics that is used to test and train the proposed approach; also a proper ANN model is built to address the problem. Age estimation through machine intelligence is a complex and demanding task. An individual is different in terms of aging, which cannot be known by his gene, but other factors also contributes such as the fitness, living approach, working style and sociality. Different ages have different forms of aging. The shape change (craniofacial growth) is visible in early years to teens; gradually the size of the face gets larger in later years. The major growth change noticeable is skin aging (texture change) which happens while aging from youth to adulthood.

The change in shape is a continuous process, but as the age increases its not significant. Therefore, facial aging is unruly and adapted. Males and females aging patterns are different, mainly because of cosmetics used by females that are likely to show younger appearances.

The paper is planned in the following manner: Section II discusses contribution from researchers in terms of feature extraction and classification problem. Section III elaborates the approach proposed for feature extraction by applying statistical methods Section IV illustrates the experimental results on applying the method. Section V provides the conclusion of the result.

### 2.0 RELATED WORK

Yen et al. [1] proposed a scheme based on allocation of values generated with the edge density of the given image. In the initial stage a face is anticipated to an ellipse, and genetic algorithm is applied to look for the best ellipse region to go with. In the subsequent extraction of feature, genetic algorithm is applied to the predefined sub regions such as eyes, nose and mouth.

Ramesha et al.[2] proposed age classification algorithm with extracted features using small training sets which gives improved results even if one image per person is available. It is a three stage process which includes preprocessing, feature extraction and classification. The facial features are identified using canny edge operator for detecting facial parts for extraction of features, and are subjected to classification using Artificial Neural Network.

Gu et al.[3] proposed automatic extraction of feature points from faces. A possible approach to find the eyeballs, close to and distant corners of eyes, center of nostril, and corners of mouth was adopted. Suo et al.[4] represented a compositional model using hierarchical And – Or graph that shows face in a

<sup>1</sup>Dept. of Computer Applications, Shri Shankaracharya Technical Campus, Chhattisgarh, INDIA.

<sup>2</sup>Dept. of Computer Applications, SSTC, Junwani, Bhilai, Chhattisgarh, INDIA.

<sup>3</sup> Dept. of Electronics& Telecommunications, Bhilai Institute of Technology, Chhattisgarh, INDIA.

Email: <sup>1</sup>sreejit.bhilai@gmail.com

particular age group. In this method the And nodes disintegrate a face into parts to reveal details (e.g., hair, wrinkles, etc.) crucial for age perception and Or nodes represent variety of faces by applying different selection. Quantitative statistical analysis validates the performance of aging model and age estimation algorithm.

Ramanathan et al.[5] developed a transformation model that formulates the shape as a physical parametric muscle model that confines the delicate changes facial features go through with growing age.

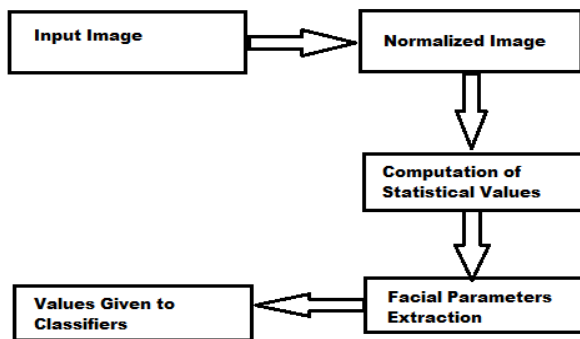
Andreas Lanitis et al.[6] generated a model of facial appearance that uses statistical methods. It was further used as the source for generating a set of parametric depiction of face images. Based on the model classifiers were generated that accepted the form of representation given for the image and generate an approximation of the age for the face image. With the given training set, based on different clusters of images, classifiers for every age group were used to estimate age. Thus as given requirement in terms of age range the most appropriate classifier was selected so as to compute accurate age estimation.

**3.0 OVERVIEW OF OUR APPROACH**

In our approach to facial feature extraction we select the input image and crop the image, the cropped image is then normalized in shape and texture for further processing.

After these pre processing done to the input image we compute the mean value within the cropped image area and the number and area in pixels of the normalized image. The normalized image is then applied for feature extraction by using facial parameters.

The facial model in our approach Geometric Facial Measurement Model (GFMM) has various landmark points which comprise the feature set for further analysis using ANN classifiers as shown in figure 1. The facial model with parameters is revealed in figure 2.

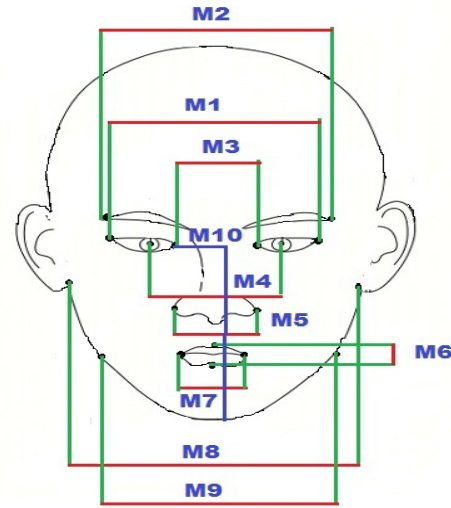


**Figure 1. Diagram for performing GFMM**

The details of each feature ID in the figure 1 is elaborated in table 1.

These facial parameters are used to measure the distance between the given points for the various subjects in our

FGNET facial aging database. The computed values are then organized in different groups for classification of age.



**Figure 2. Facial Feature parameters**

**Table 1. Illustrates Facial Features in the Model**

Feature Id	Feature parameter
M1	Extreme ends of left and right eye
M2	Extreme ends of left and right eyebrow
M3	Left and right eye points between nose
M4	Between left and right iris
M5	Nose end points
M6	Lips vertical measurement
M7	Lips horizontal measurement
M8	Ear points left and right
M9	Cheek points left to right
M10	Vertical measurement from nose

**3.1 Mathematical Formulations**

After we cropped the image it is subjected to normalization which is further processed to estimate the area. The value is a scalar that corresponds to the entire pixel number in the normalized image, at times it may not be the same because pixels with varied patterns are weigh differently. We use these values to compute Mean, each row or column of the input with the vectors of a particular dimension of the input, or complete.

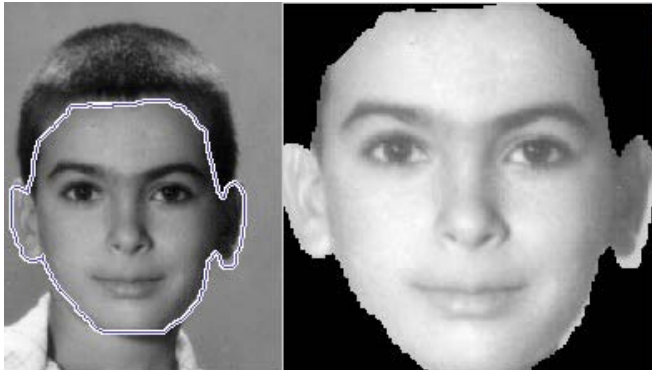
**4.0 EXPERIMENTAL RESULTS**

**4.1 Database for Aging**

The Face and Gesture Recognition Research Network (FG-NET) is a database of face images of persons at their different ages. FG-NET is widely preferred for age related research works, because it contains 1,002 images of high resolution color or gray scale for performing various tasks. The age of

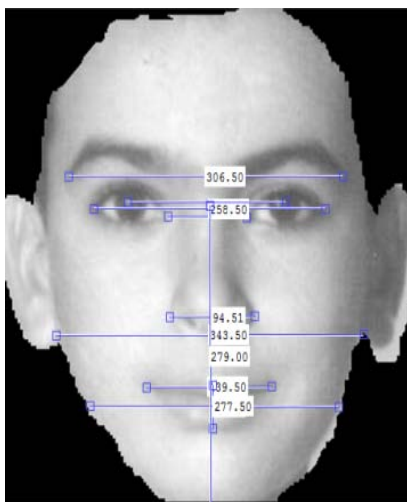
persons in database varies from 0 to 69 years in chronological order of their aging. It comprises of 82 multiple race images with difference of lighting, pose and different expressions. The main effort to develop such a database was to help the researchers who perform various operations on facial image to study the aging effects. The database is available for free access for research purpose.

The approach used is implemented to FGNET aging database. The GFMM is a graphical based implementation for feature extraction from input image. The original input image and normalized image is shown in figure 3.



**Figure3. Cropped and Normalized Image for Processing.**

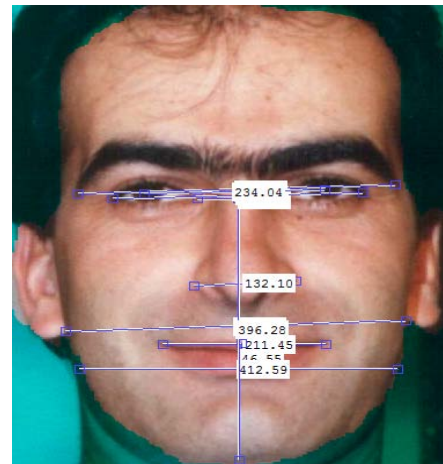
The normalized image is subjected for feature extraction here the distance between the points given in the feature ID is selected. After plotting all the facial feature parameters the values are computed for age classification problem. The figure 4 shows the facial feature parameters with their values.



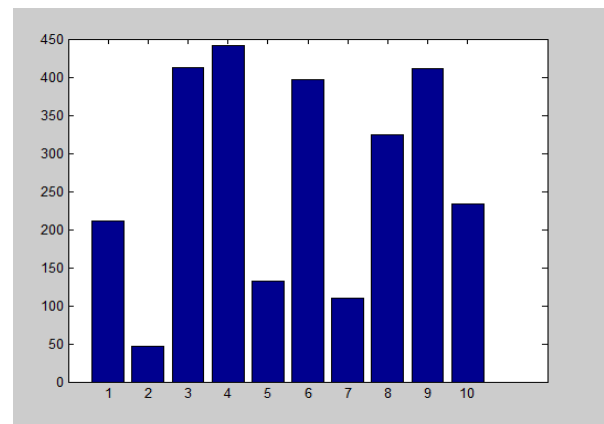
**Figure4. Facial Feature Extraction.**

The computed values are plotted for further analysis of the feature which is considered in different age groups. Broadly four groups are identified in which different images from FGNET database are subjected to further classification. The

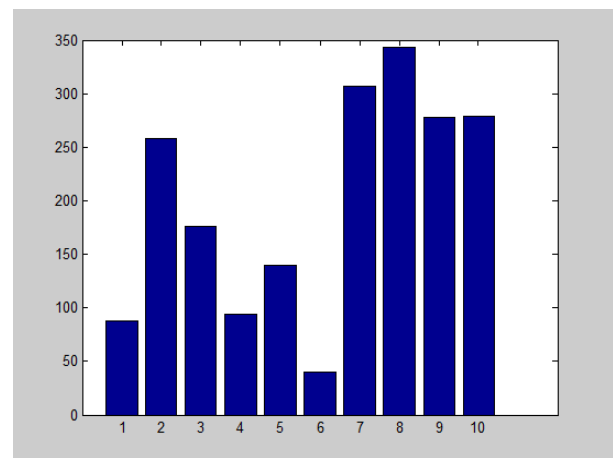
difference in values computed are evident from the graphs plotted against the values of figure 4 and 5 as shown in figure 6 and 7 respectively.



**Figure5. Facial feature extraction by GFMM**



**Figure6. Graph plotted against figure 4 values.**



**Figure7. Graph Plotted against figure 5 values.**

**4.2 Training with FGNET Dataset**

In training we have used 101 images of different subjects with varying ages, in all age groups. We have classified four groups child, young, middle aged and old aged. The results of the training the input with its computational efficiency is made known in table 2

**Table 2. Outcome on FGNET Database.**

Performance parameter	Values (%)
accuracy	82%
sensitivity	84%
specificity	81%
Recall	74%
precision	84%
f_measure	85%
gmean	82%

**5.0 CONCLUSION AND FUTURE SCOPE**

The proposed approach is based on facial features for age estimation using Geometric Facial Measurement Model (GFMM). Our proposed method of finding facial features is different from other researchers. We have considered different facial parameter points through which we computed the statistical values. Normally the facial feature depends on 68 landmark points taken from facial images [7]. To test our system, we used FGNET aging database. A comparative learning has been carried out between different age group to assess the output of our projected system. It is evident from the training output that the proposed system performs closer to the human's judgment to identify age. In the testing phase, images are classified, while classification identification rate of the method is 85.6, on comparing this result with the human perception to age it exhibits a minor deviation to actual. It is evident from the study that performance of the system is near to values that is available in the database of aging used for classification.

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