Fusion of Structural and Textural Facial Features for Generating Efficient Age Classifiers

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ABSTRACT

Facial aging is a usual happening that is certain, and varies from person to person depending upon the circumstances and living habits. Applications of age determination are observed in domains like forensic science, security and also to determine health. Facial parameters used for age classification can be either structural or textural. In this paper we have used both approaches for feature extraction. In structural, facial growth is considered for classification, by computing the Euclidean distance between the various landmarks on facial image. 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. In textural approach we consider skin texture for classifying the age groups. The prominent areas in facial skin are extracted where significant changes occur in terms of wrinkles that happen in the process of aging. Local Binary Pattern (LBP) feature is used for classification of age in different groups. The experimental results are significant and remarkable.

CCS Concepts

Computing Methodologies→ Artificial Intelligence→Computer Vision.

Keywords

Aging, Age Estimation, Texture.

1. INTRODUCTION

The current technology in information processing via computer systems has immensely reduced the complexity of Human - Machine interaction. The Aging starts at the age of twenty five, when the first signs become visible on the facial skin. In the very beginning a fine line appears which gradually turn to wrinkles, and over time it loses its volume and density that makes it more noticeable.

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Understanding the anatomy of facial aging, the surface and subsurface known as epidermis, dermis and subcutaneous layer changes its structural form in multiple layers which includes fat and muscle. In the process of aging, skin changes its texture such as thinner skin, drier skin, less elastic skin, wrinkle and reduction in collagen. To achieve our goal we have created a database of feature set, used to train and test the proposed; also a proper ANN model is build to address the problem.

Age estimation through machine learning 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. Determining the age of human through facial parameters using various approaches in the field of computer vision and pattern recognition have gained considerable importance in recent times. [3],[7],[8]. 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.

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. Considering the facial features as parameter for gender recognition and expressions, researchers have carried out their work in this field. The age estimation and classification with facial features has gained significance among researchers.

The paper is prearranged as follows: Section 2 discusses contribution from researchers in terms of feature extraction and classification problem. Section 3 is about the approach used for feature extraction by using statistical methods. Section 4 shows the investigational results by applying the method. Section 5 provides the conclusion of the result.

2. RELATED WORK

Duong et al. [1] proposed a combination of both global and local features using Active Appearance Model (AAM) and LBP approach, in which LBP for the images in FGNET was used for binary classifier to identify youth from adults using Support Vector Machine (SVM).

Ramanathan et al. [9] proposed an image gradient based texture transformation function that distinguishes facial wrinkles often seen during aging. The rate of wrinkles visible for individuals varies from person to person. Jana et al. [5] proposed a technique, which provides a robust method that validates the age group of individuals from a set of different aged face images. The vital features such as distances between various parts of face, analysis of wrinkle characteristics and computation of face position are observed.

Yen et al. [12] proposed a methodology based on the edge density distribution of the image. In the pre-processing stage a face is estimated to an ellipse, and genetic algorithm is applied to look for the finest ellipse region to match. In the feature extraction stage, genetic algorithm is applied to find out the facial features, which include the eyes, nose and mouth, in the earlier defined sub regions.

Jana et al.[4] It provides a method to calculate the age of human by analyzing wrinkle area of facial images. Wrinkle characteristics are detected and features are extracted from facial images. Depending on wrinkle features, facial image is grouped using fuzzy c-means clustering algorithm.

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 computed 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.

Ramesha et al.[10] 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.[2] 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.[11] it represented a compositional model using hierarchical And – Or graph that shows face in a 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 observation and Or nodes signify array of faces by applying different selection. The performance of aging model and age estimation algorithm is validated using statistical analysis.

3. METHODOLOGY

3.1 Local Binary Pattern

The transformation of an image into an array depicting small scale appearance of the given image is carried out using Local Binary Pattern operator. The threshold values with weights of the corresponding pixels are multiplied and then added up to get the result, known as LBP code for a given neighborhood.

For texture analysis we implemented the statistical or stochastic approach, considers texture as a statistical event. The texture formation is shown as statistical properties of the intensities and positions of pixels. LBP may be considered as a multidimensional co-occurrence statistic.

This formulation of texture is based on a model that depicts texture as a sample of a two-dimensional stochastic process that can be described by its statistical parameters. The changes in values that mathematically correspond to a derivative is referred as texture. Thus by subtracting the values of neighbors with the centre value and then dividing by distance we find the first derivative in each direction (1).

$$LBP_{P,R}(x_c, y_c) = \sum_{P=0}^{P-1} s(g_p - g_c)\, 2^P \quad (1)$$

Where
g_c is the grey value of the center pixel.
P is number of grey value neighbors.
R is radius.
S is the step function.
2^P binomial weight.

3.2 Our Approach

In order to extract the local and global features from facial images we applied the LBP and distance vector for respective feature extractions. The images are subjected to pre-processing which includes resizing the images for uniformity and accuracy. During the process, filter is implemented for removing the noise that further enhances the result. The computed values from both the approach are used to train the network. The block diagram for local feature extraction approach is shown in (see Figure 1).

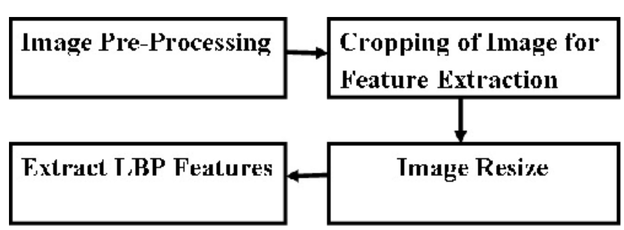

Figure 1. Block diagram for the approach.

After the pre-processing it is subjected for feature extraction at the specified areas where the wrinkles are prominent. The areas considered for local feature extraction is shown in (see Figure 2).

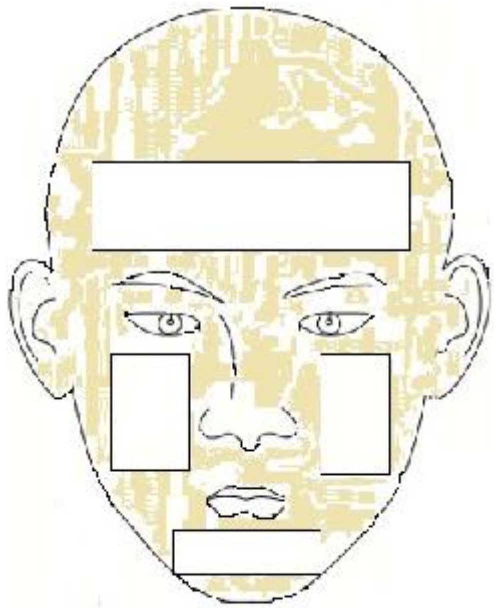

Figure 2. Local feature extraction regions.

The cropped regions are computed for Local Binary Patterns, thus for a single image four feature sets are computed. This process is illustrated by the (see Figure 3).

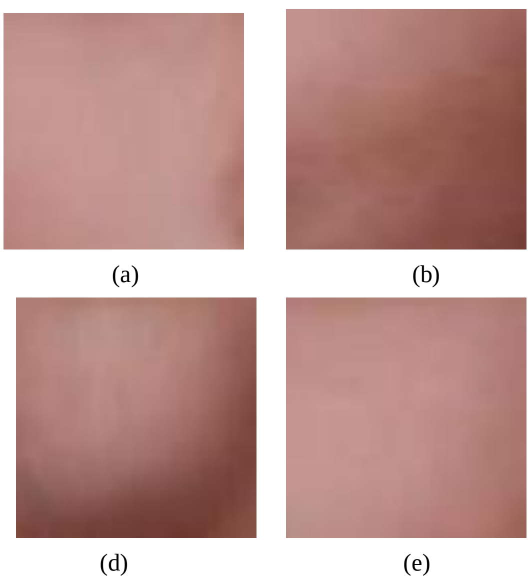

Figure 3. (a) Forehead texture (b) & (c) Cheek region (Left & Right) (d) Chin region texture.

After cropping of images as per the model proposed these images are further computed for feature values using local binary pattern. The output for these transformations is shown (see Figure 4).

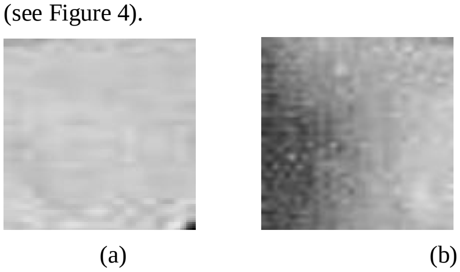

Figure 4. After computing the LBP Features. (a) Forehead texture (b) & (c) Cheek region (Left & Right) (d) Chin region texture.

The extracted features are subjected to classification using ANN, where these features are computed for different age groups (see Figure 5). To narrow down the results and more accurate results to be predicted, six groups are identified from the FGNET aging database.

In total 97 images were taken and the approach was tested with this dataset.

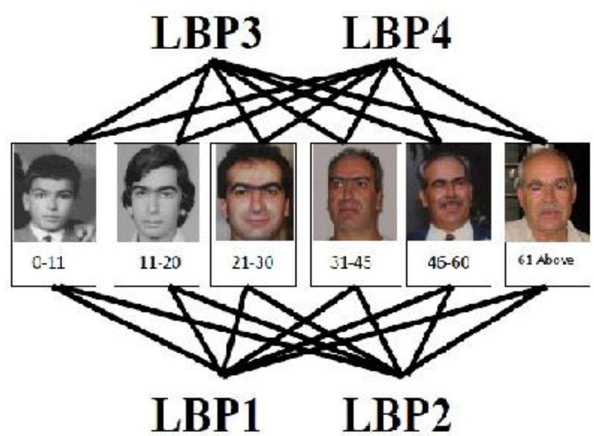

Figure 5. LBP features for different age groups.

3.3 Global feature Extraction

The input image is cropped and then subjected to pre-processing to have uniformity in size and shape of the images. After these pre processing done to the input image we compute the mean value within the cropped image area. The cropped 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 (see Figure 6).

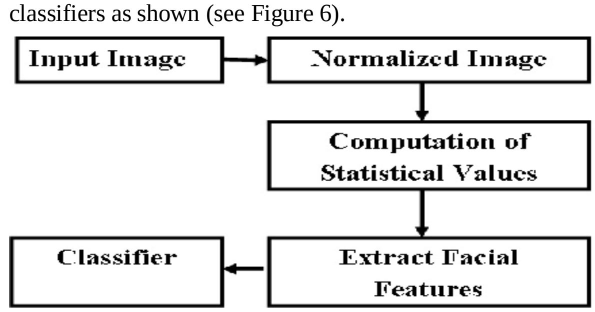

Figure 6. Diagram for performing GFMM.

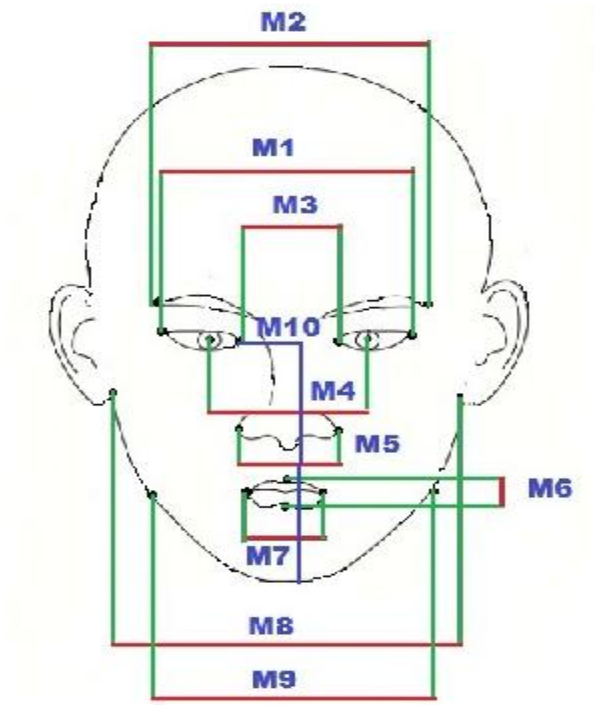

Figure 7. Facial Feature parameters.

The facial model with parameters is revealed in (see Figure 7). The details of each feature ID is elaborated in (Table 1).

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

These facial features are used to compute the distance between the given points for different persons in our FGNET facial aging database. The computed values are then structured in different groups for age classification.

3.4 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.

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 8).

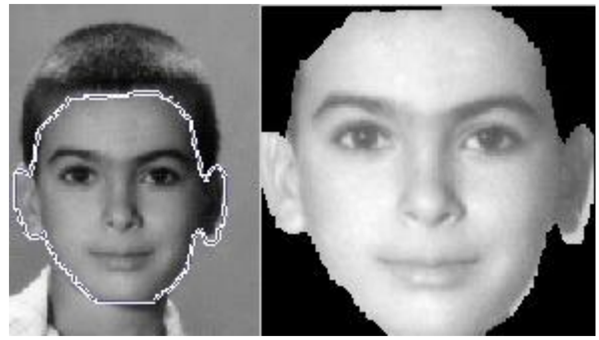

Figure 8. Cropped and Normalized Image for Processing.

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 (see Figure 9) shows the facial feature parameters with their values.

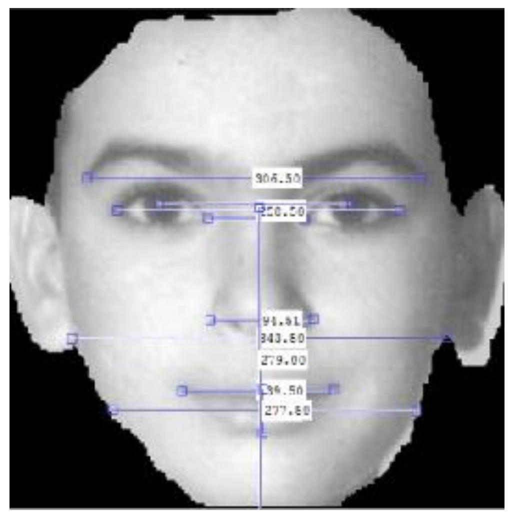

Figure 9. Facial Feature Extraction.

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 (see Figure 9 and 10) as shown in (see Figure 11 and 12) respectively.

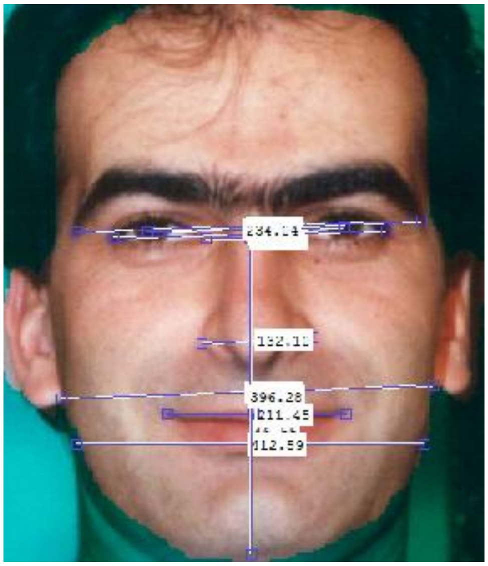

Figure 10. Facial feature extraction by GFMM.

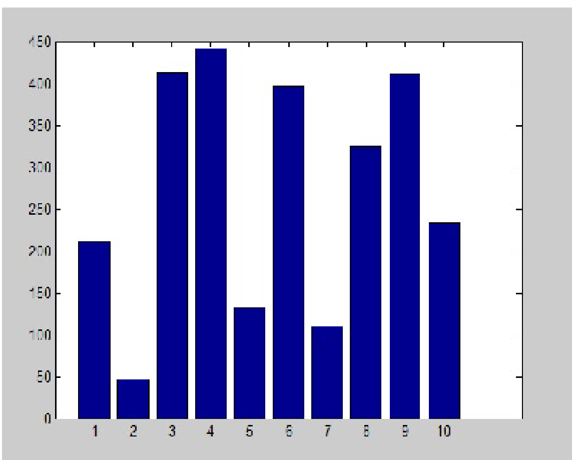

Figure 11. Graph plotted against figure 9 values.

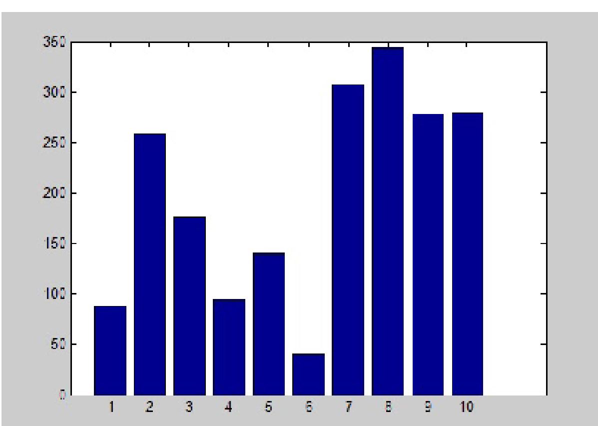

Figure 12. Graph Plotted against figure 10 values.

3.5 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 an 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.

4. EXPERIMENTAL RESULTS

4.1 Training with FGNET dataset

In training 97 images of different subjects with varying ages, in all age groups are considered. Six groups are classified in the range (0-11), (11-20) , (21-30), (31-45), (46-60) and (61 above). The results of the training the input with its computational efficiency is shown in (Table 2).

Table 2. Results on FGNET Database.

Performance parameter	Mathematical Formulation	Values (%)
Accuracy	(Tp+Tn)/(Tp+Fn+Fp+Tn)	84.16%
Sensitivity	Tp/(Tp+Fn)	84.62%
Specificity	Tn/(Tn+Fp)	84.00%
Recall	Tp/(Tp+Fn)	71.24%
Precision	Tp/(Tp+Fp)	84.53%
F_measure	2*((precision*recall)/(precision + recall))	73.33%
Gmean	sqrt(Sensitivity * Specificity)	84.31%

Tp — Number of true positive case
Fn — Number of false negative case
Fp — Number of false positive case
Tn — Number of true negative case

5. CONCLUSION

The proposed approach is based on Local Binary Pattern and distance vector for extracting local and global facial features for age classification. Our proposed method of finding facial features is different from other researchers. We have performed pre-processing to the images in FGNET which include resizing and filtering to improve the efficiency of the classifier. The number of age groups is more compared with others, thus tried to get more accurate results from the experiments done with this approach.. 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, we found that the accuracy of the classification for various age groups is 84.16, thus on comparing this result with the human perception to age it exhibits a minor deviation to actual. As number of groups considered is more which gives better accuracy on comparing with other research traits. It is evident from the study that performance of the system by performing fusion of both local and global is remarkable.

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