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Age Group Estimation using Facial Features

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Abstract: Human face is the non-verbal portal into the person. A person's gender, mood, country of origin, age category, and identity can be identified from the face. There has been a growing interest in automatic age estimation from facial images due to a variety of potential applications in law enforcement, security control, and human computer interaction (HCI). This paper presents a method to improve the accuracy of the estimated age. Apart from geometric shape features, wrinkle analysis is also incorporated in classifying the age. Multiple algorithms are applied for different phases like feature extraction, illumination correction, image fitting and edge detection etc. The main objective of this paper is to present a working model of an age classifier that is more efficient than the existing models. The experimental results show that 93.01% recognition rate can be achieved when applying the proposed system on the images.

Keywords: Edge detection, Age classifier, geometric shape features, wrinkle analysis, feature extraction, illumination correction.

I. Introduction

The research in the field of image processing has undergone a rapid growth with the ability to solve the real world problems. Those researches include applications in tracking down a vehicle in an image, facial recognition, authentication purposes such as debit/credit cards, passports, voter's identification cards etc. Among these there are several applications that use the image of the user as the input and perform various operations on them. This paper presents an overview of the prior works in age estimation (determination) and a novel approach based on a hierarchical model, which infuses a classification system with multiple age estimator functions to create an industry age-estimation algorithm. It is a well-known fact that the biodynamic factors of facial aging are quite different for the two stages of aging: growth and development and adult. During the latter, the major changes in facial complex are due to lengthening and widening factors of cranial complex. The aging factor for adults does include some cranial changes, but the primary drivers are the development of wrinkles, lines, creases, and sagging of the skin.

There are various methods used in this paper for age group estimation techniques that are currently deployed in areas like features extraction, age classification and texture analysis and the suitable algorithms are selected that efficiently suits the current needs.

II. Earlier Works

The active appearance model (AAM) is used to estimate age as facial global features. The AAM is a generative parametric model that contains both the shape and appearance of a human face, which it models using the principal component analysis (PCA), and is able to generate various instances using only a small number of parameters. Therefore, an AAM has been widely used for face modelling and facial feature point extraction. Active Appearance Model, which is the extension of Active Shape Model, finds the feature points using the improved Least Mean Square Method. Then Support Vector Machine method is applied to create hyper planes that will act as the classifiers. Using the result, the person is classified as young or adult. Two separate aging functions are developed and used to find the age as proposed by K. Luu et al. [4] and Choi et al. [9]. The method proposed by K. Ricanek et al. [5] can be considered as the extension of K.Luu et al. [4], with the exception that Least Angle Regression (LAR) method is used to increase the accuracy of finding the feature points in the image using AAM. In LAR method, all the coefficients are initially assigned 0. Then from feature point x_1 , LAR moves continuously towards least mean square value until it reaches the efficiency.

Global features such as distance, angle and ratio are also considered for classification of age group. Merve Kilinc et al. [6] use a new method of having overlapped age groups and a classifier that combines geometric and textural features. The classifier scoring results are interpolated to produce the estimated age. Comparative experiments show that the best performance is obtained using the fusion of Local Gabor Binary patterns and Geometric features. From the geometric features, the cross-ratio is found out, which the ratio of distance between the facial features like nose ends, chin, head, jaw. The role of geometric attributes of faces is considered, as described by a set of landmark points on the face, in the perception of age. The affine transformations used to approximate change in the pose of the subject. Subspaces can be identified as points on

a Grassmann manifold. The warping of an average face to a given face is quantified as a velocity vector that transforms the average to a given image in unit-time. Then Euclidean space regression method is applied. This paper concerns with providing a methodology to estimate age groups using face features. This method is based on the face triangle which has three coordinate points between left eyeball, right eyeball and mouth point. The face angle between left eyeball, mouth point and right eyeball estimates the age of a human. On human trial, it works well for human ages to 18 to 60 as discussed by P. Turaga *et al.* [7] and R. Jana *et al.*[8].

Choi *et al.* [9] discusses about the age detection using age feature classification combined in order to improve the overall performance. In feature extraction, they discussed about the local, global and hierarchical features. In local features such as wrinkles, skin, hair and geometrical features are extracted using Sobel filter method. In global features AAM method, Gabor Wavelet transform methods are used. Hierarchical is the combination of both the local and global features. In proposed model they use Gabor filter to extract the wrinkles and LBP method for skin detection. This improves the age estimation performance of local features.

C. T. Lin *et al.*[11], estimated the age by global face features based on the combination of Gabor wavelets and orthogonal locality preserving projections. The feature selection is based on Harr features and Adaboost method for strong classifier. The Gabor wavelet transformation is used to increase efficiency of SVM construction. Hu Han *et al.*[12] discussed about the face pre-processing, facial component localization, feature extraction and hierarchical age estimation. They use SVM-BDT (Binary Decision Tree) to perform age group classification. A separate SVM age repressor is trained to predict the final age.

III. Proposed method

A. Architecture Diagram

The architecture diagram of the proposed model for age group estimation using facial features is shown in Fig 1.

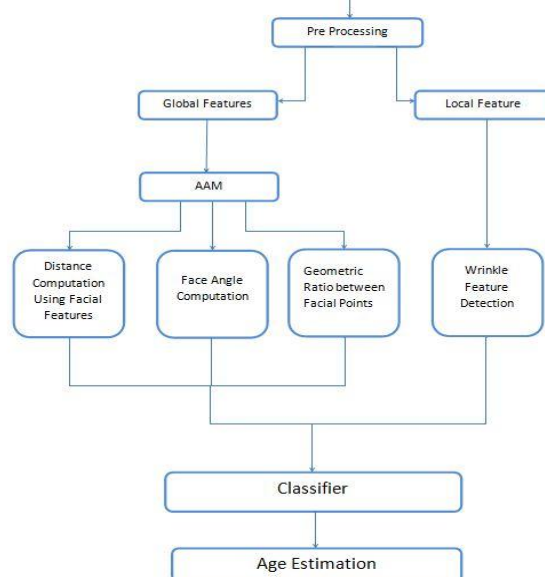


Fig. 1 Architecture diagram for the proposed method

B. Pre processing

1. Illumination

The contrast of the input image is enhanced using its histogram. The input image is transformed into frequency domain using Discrete Cosine Transform and is used to get the areas affected by illumination. Those areas are normalized using power law transformation, using the gamma value as proposed by C.Arun Kumar *et al.*[1] shown in the Fig. 2. The pre processed image is now sent for feature extraction of both global and local features.



Fig. 2 Histogram Equalization (Left: Original Image, Right: Histogram equalized image)

2. Global features

2.1 Feature Extraction using Active Appearance Model

Active Appearance Model (AAM) is particularly suited to the task of interpreting faces in images. The shape of a face is represented by a vector consisting of the positions of the landmarks. All shape vectors of faces are normalized into a common coordinate system. The shape of an independent AAM is constructed by a mesh of 68 points. AAMs are normally computed from hand labelled training images. This approach is to apply Principal Component Analysis (PCA) to the training meshes of 68 points. AAM analyzes the gray level of the particular feature point. The gray level of each and every 68 feature points are analyzed in the same way and these 68 feature points are used mainly for collecting the attributes of all the distance, ratio and angle classification.

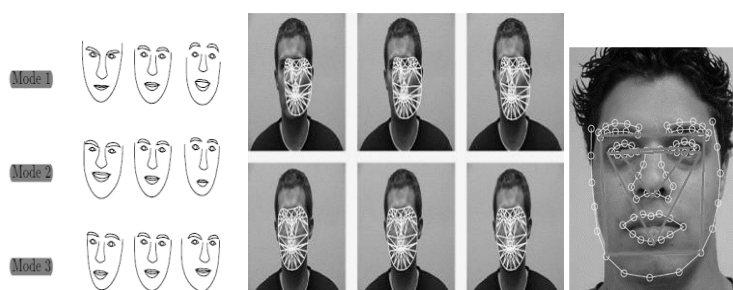


Fig. 3 Feature extraction using Active Appearance model

The AAM applied image is now classified using distance, angle and ratio computation.

2.2 Classification using Distance Computation

The 18 facial features points are identified from the AAM applied image and then 15 facial features distance between selected feature points are calculated as shown in Fig. 4. Most of the selected feature points are related to the mouth, nose, eye and eyebrow. There are eight distances respect to horizontal axis and seven distances respect to vertical axis on the facial image. Those distances are (a) Eye length (b) Eye inner corner distance (c) Width of the mouth (d) Eyebrow length (e) Left to Right Eyebrow (f) Width of the face (g) Width of nose (h) Bottom width (i) Mouth to bottom (j) Nose to bottom (k) Top to bottom (l) Eye height (m) Top to nose (n) Lip height (o) Top to lip.

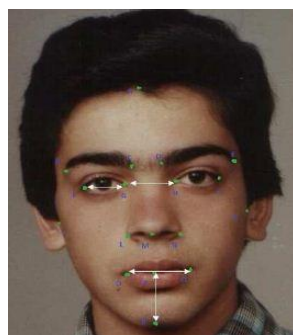


Fig. 4 Distance computation for input image

2.3 Classification using Face angles

The facial features points are identified from the AAM applied image and then from the obtained facial features, four angles are found. The four angles that are computed for the points as follows:

- angle from eyes to nose,
- angle from eyes to mouth,
- angle from eyebrows to mouth
- angle between eyes, nose and mouth

Each of the four angles is found by drawing a triangle for the respective points and slopes are calculated as m_1 and m_2 . From the slopes m_1 and m_2 , the face angle (A) is calculated using the formula

$$A = \tan^{-1}((m_1 - m_2)/(1 + m_1 * m_2)) \quad (1)$$

These four angles are taken as feature points combined with the attributes obtained from distances and ratios calculations to classify the images under four age groups.

2.4 Classification using Ratios

Similar to the computation of the angles and distances, the facial features points are identified from the AAM applied image and then from the obtained facial features, the eight ratios are calculated using the image shown in Fig. 5.

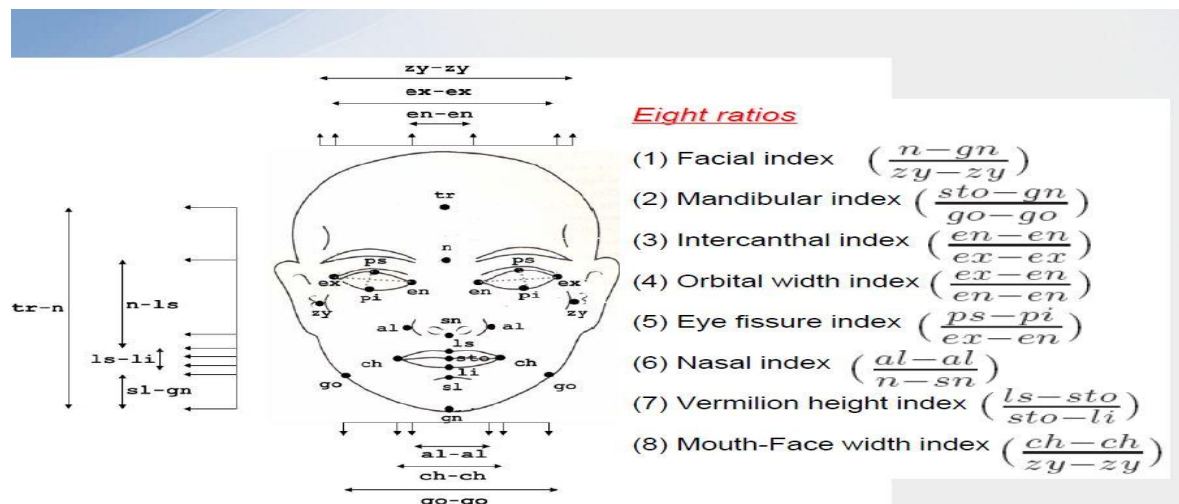


Fig. 5 Ratio calculation from the input image

3. Local features

3.1 Feature extraction using wrinkles

Each type of wrinkle has their own orientation and it is good to apply gabor filter for that particular angle. The mean, variance, standard deviation will give the details of the feature in the wrinkle areas. In case of PCA, the maximum support vector will give the feature of the wrinkle. The facial parts to be considered are shown in Fig. 5.

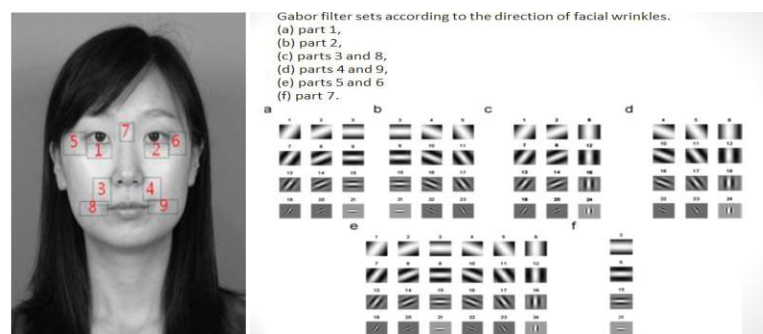


Fig.6 Regions to be considered and Gabor filter's angles

To determine the wrinkle features, we use the mean and variance of the magnitude response of the Gabor filter in each wrinkle area, because the mean and the variance of the magnitude represent both the strength and quantity of wrinkles.

4. Classification Analysis

All the attributes obtained from both the global and local features are integrated and loaded into the classifier in WEKA tool. The classifier used is NNge (Non Nested Generalized Exemplar) with loaded training set from the FG-Net database. This classifier is used because of reduced error rate and high accuracy level when compared to the other classifiers. This classifier gives accuracy of up to 93.01% as shown in the Fig. 6. Totally 216 out of 229 instances are classified into correct age groups 0-19, 19-29, 29-39 and 40 above.

Time taken to build model: 0.09 seconds

=== Evaluation on test set ===
=== Summary ===

Correctly Classified Instances	213	93.0131 %
Incorrectly Classified Instances	16	6.9869 %
Kappa statistic	0.8776	
Mean absolute error	0.0349	
Root mean squared error	0.1869	
Relative absolute error	12.2791 %	
Root relative squared error	49.8376 %	
Total Number of Instances	229	

=== Confusion Matrix ===

a	b	c	d	<-- classified as
140	2	0	0	a = 1
0	28	14	0	b = 2
0	0	25	0	c = 3
0	0	0	20	d = 4

Fig. 7 NNge Classifier analysis

IV Conclusion and Future Work

In this project the age group is estimated by computation of face angles, distances between facial feature points, ratios and wrinkle detection is demonstrated and how these components are used to classify the age is analyzed in detail. We included nearly 34 attributes calculated from these components if they vary linearly (or close to being linear) with age. The main challenge lies in identifying the best combination of these components (distance, ratio and angle). Future work involves in selection of best combination of features that will help in liberalizing the values which will automatically improve the efficiency of the classifier.

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