2nd International Conference on Science, Technology and Management
University of Delhi (DU), Conference Centre, New Delhi (India)
27 September 2015, www.conferenceworld.in, www.icstmdu.com
978-81-931039-6-8

HUMAN AGE ESTIMATION BY GABOR & FUZZY K-MEANS

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ABSTRACT

In this Research paper, a new automatic age estimation framework is proposed. A single image is required as input for the subject of interest to estimate his age. The framework is composed of three main modules: 1) the face detection module; 2) the enhancement module; and 3) the classification module. The face detection module comprises the main blocks of image representation and learning for age estimation. For age image representation, a technique named adaboost which is modification of viola Jones algorithm is used. In classification module unsupervised classification technique is used. K means algorithm is used which classified the features obtained from the Gabor filters of 4 scales and 6 directions. In the enhancement module of the proposed framework, facial regions that are keys for age estimation are identified through a more detailed analysis. Finally, a human age estimation application is built by utilizing the FG-net database.

Keywords: Age Estimation, Adaboost Algorithm, Gabber Filter, Face Detection, Feature Extraction. Feature Classification.

I. INTRODUCTION

The human face holds important amount of information and attributes such as expression, gender and age. Aging is non-reversible process. Human face characteristics change with time which reflects major variations in appearance. A 30 years old person who smokes a box of cigarettes each day will look like 42 years old one compared with other facial characteristics such as identity, expression and gender. Our work is revolving around the three modules: face detection, features extraction and features classification.

1.1 Overview of Proposed Age Estimation System

An overview of our age estimation system, which considers the effects of gender and/or facial expression for the preprocessing step, the face and eye positions are first detected from the input image using adaptive boosting (AdaBoost) method. Adaboost method will be used to select the face region used for features extraction which will mainly exclude hairs, and then histogram equalization of facial image will be done to counter non illumination of light. Geographical features of image like eye to eye distance, center of left eye to nose, center of right eye to nose and face angle are calculated along with wrinkles features on images which are global features. These features are global features and obtained by using Gabor filters with specific number of angles and

orientations. Amongst classification algorithms, clustering algorithms serves better. So fuzzy-K means approach will be used for it and results will be obtained in terms of MAE.

1.1.1 Adaboost Method

The basic problem to be solved is to implement an algorithm for detection of faces in an image. AdaBoost algorithm developed by Freund and Schapire in 1996 [5]. AdaBoost is a machine learning boosting algorithm capable of constructing a strong classifier through a weighted combination of weak classifiers. (A weak classifier classifies correctly in only a little bit more than half the cases.) To match this terminology to the presented theory each feature is considered to be a potential weak classifier. A weak classifier is mathematically described as:

$$h(x,f,p,\theta) = \begin{cases} 1 \; if \; pf(x) > p\theta \\ 0 \; otherwise \end{cases}$$

Where x is a 24*24 pixel sub-window, f is the applied feature, p the polarity and θ the threshold that decides whether x should be classified as a positive (a face) or a negative (a non-face). Since only a small amount of the possible 160.000 feature values are expected to be potential weak classifiers the AdaBoost algorithm is modified to select only the best features. AdaBoost algorithm in place it seems like the face detector is ready for implementation, but Viola-Jones has one more ace up the sleeve.

1.1.2Gabor filter

A Gabor filter is a linear filter whose impulse response is defined by a harmonic function multiplied by a Gaussian function. Gabor filters are directly related to Gabor wavelets, since they can be designed for number of dilations and rotations. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. Gabor filters have been used in many applications, such as texture segmentation, target detection, fractal dimension management, document analysis, edge detection, retina identification, image coding and image representation. A Gabor filter can be viewed as a sinusoidal plane of particular frequency and orientation, modulated by a Gaussian envelope.

h (x, y) = s(x, y)g(x, y)

s(x, y): Complex sinusoid

g(x, y) : 2-D Gaussian shaped function, known as envelope

$$s(x,y) = e^{-j2\pi(\omega_0 x + v_0 y)}$$

$$g(x,y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)}$$

The Gaussian envelope looks as follows:

$$\omega_r(x,y) = K \exp\left(-\pi(a^2(x-x_0)_r^2 + b^2(y-y_0)_r^2)\right)$$

1.1.3K-Means Clustering Algorithm

In our work k-means clustering algorithm is used as unsupervised learning for of clustering of features. This is the simplest algorithm, easy to implement and based on the criteria of minimum distance between cluster head and points in that cluster and maximum distance of nodes with other member nodes of other cluster The fuzzy *k* means clustering (FKM) algorithm performs iteratively the partitionstep and new cluster representative generation step until convergence.

The distance between the data points is calculated using Euclidean distance as follows. The Euclidean distance between two points or tuples, X1 = (x11; x12 : : : x1n), X2 = (x21; x22 : : : x2n)

$$Dist(X_1 X_2) = \sqrt{\sum_{i=1}^{n}(x_{1i} - x_{2i})^2}$$

This k means algorithm clusters all nodes and completes our last module to classify the image data.

II. LITERATURE SURVEY

[1]Jana, R. et. al. [2012] concerned with providing a methodology to estimate age groups using face features. This paper proves that face angle can estimate and classify human age according to face features extracted from human facial images. **[2]Jana, R. et. al. [2013]** estimated age group using face features. This process involves three stages: Pre-processing, Feature Extraction and Classification. This paper can be used for predicting future faces, classifying gender, and expression detection from facial images. **[3]Lazarus, M.Z. et. al [2013**]proposed in this article is capable of segregating the given input images into three clusters namely: Baby; Adult; Senior The database used in this is FG-NET database available online and results have shown the 100 percent accuracy**.[4] Otto, C. et.al [2012]** propose a component based method for age invariant face recognition**.[7] Ricanek Jr., K. et.al. [2006]** provided details MORPH a longitudinal facedatabase developed for researchers investigating allfacets of adult age-progression. **[9]Chang, K.U. et.al [2010]** proposed a ranking-based framework consisting of a set of binary queries. [10].Ylioinas, J, et.al [2012] proposed a novel method for age classification. Our proposed method is based on a combination of local binary pattern (LBP) variants encoding the structure of elongated facial micro-patterns and their strength thus allowing a fair comparison and an easy reproduction of the results **[11].Nguyen, D.,T. et. al [2014]** investigated the effects of gender and facial expression on age estimation using support vector regression (SVR) method. This research is novel in the following four ways. First, the accuracies of age estimation using a single-level local binary pattern (LBP) and a multilevel LBP (MLBP) are compared, and MLBP shows better performance as an extractor of texture features globally. Second, we compare the accuracies of age estimation using global features extracted by MLBP, local features extracted by Gabor filtering, and the combination of the two methods. Results show that the third approach is the most accurate. Third, the accuracies of age estimation with and without pre-classification of facial expression are compared and analyzed. Fourth, those with and without pre-classification of gender are compared and analyzed. The experimental results show the effectiveness of gender pre-classification in age estimation **[12] Iraji, M.S. et.al [2014]** presented an intelligent model to estimate the age of face image. They used shape and texture feature extraction from FG-NET landmark image data set using AAM (Active Appearance Model), CLM (Constrained Local Model), tree Mixture algorithms. Experimental results showed that in proposed system, fuzzy svm has less errors and system worked more accurate and appropriative than prior methods. Our system is able to identify age of face image from different directions as is.

III. PROBLEM FORMULATION & OBJECTIVE

For age classification form facial features, two categories have been constructed for features: Global features, local features. Among global features Active appearance models (AAM) is frequently used by many researcher. But it suffers from drawback that they don't provide any information about wrinkles and skin features. Based on

wrinkle features classification is also used by many researchers but it suffers setback in case of scar on face. In that case highest number of edge points will come from scar area and that can lead to misconception. To counter this problem global and local both features are used to estimate the age. But one more hindrance which measurably affects the correct estimation and less tackled by researchers is the non- uniform illumination of face. Without compensating it, results are doubted. After features extraction, classification techniques are used to classify features in different age groups. Researchers have shown that SVM is good in classifications.

Keeping above points into consideration following will be key objective which will be followed in our work:

- Adaboost method will be used to select the face region used for features extraction which will mainly exclude hairs, and then histogram equalization of facial image will be done to counter non illumination of light.
- Geographical features of image like eye to eye distance, center of left eye to nose, center of right eye to nose and face angle are calculated along with wrinkles features on images which are global features. These features are global features and obtained by using Gabor filters with specific number of angles and orientations.
- Amongst classification algorithms, clustering algorithms serves better. So fuzzy-K means approach will be used for it and results will be obtained in terms of MAE.

IV. PROPOSED WORK

Our work is revolving around the three modules: face detection, features extraction and features classification. We have used adaboost algorithm to detect the faces. This algorithm is using strong classifier and multiple iterations to detect the face and results approached by this algorithm have been proven 99 % correct in favorable conditions. The pseudo code for adabosst algorithm is given in table 4.1.

given input image (x_l, y_l)……. (x_n, y_n)

- initialize weights $w_{,l} = \frac{1}{2m}, \frac{2}{2l}$

- For t=1…..T

1) Normalize the weights $w_{i,l} \leftarrow \frac{w_{t,l}}{\sum_{j=1} w_{t,j}}$

2) Slect the best weal classifier with respect to the

$$\varepsilon_i = min_{f,p,\theta} \sum_i w_i |h(x_i, f, p, \theta) - y_i|$$

3) Define

$$h_i(x) = h(x, f, p, \theta)$$

4) Update the weights

$$w_{i+1,i} = w_{i,i} \beta^{1-\varepsilon_i}$$

Where e_i=0 if example x_i is classified correctly and e_i=1 otherwise and $\beta = \frac{\varepsilon_i}{1-\varepsilon_i}$

5) The final strong classifier is

$$c(x) = \begin{cases} 1 \; if \sum_{i=1}^{T} \alpha_i h_i(x) \geq \frac{1}{2} \sum_{i=1}^{T} \alpha_i \\ 0 \quad otherwise \end{cases}$$

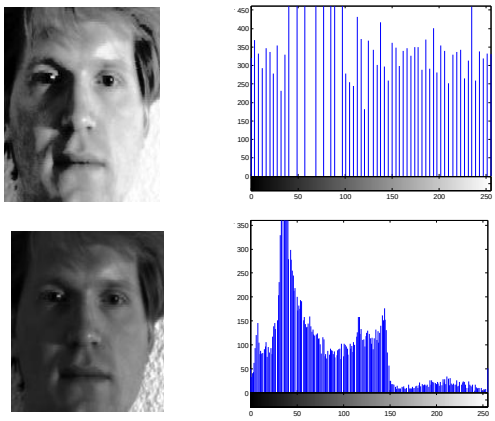


Figure 4.1: Histogram after Illumination Compensation and Before Compensation

In our work k-means clustering algorithm is used as unsupervised learning for of clustering of features. In the k-means clustering algorithm, we first load the image & then detect the face image using adabosst method. In next step this loaded image will be get cropped and run histogram equalization part to normalize the image. Generate gabor filter coefficients at 4 scale and 6 orientations using 2 dimensional gabor & so on as describe in the algorithm below:-

Begin

{

-Load the test image

-Detect the face image using adabosst method by using algorithm described in table 4.1

-Crop the face part and run histogram equalization part to normalize the image illumination variation.

-Generate gabor filter coefficients at 4 scale and 6 orientations using 2 dimensional gabor filter equation discussed in section1.1.2.

-filter the image by using real part of gabor filter

-concatenate the image features obtained from gabor filtering into single dimensional matrix

-execute k means classification module by clustering the age groups ino 10 sub groups and after multiple iterations, minimum mean square error is saved.

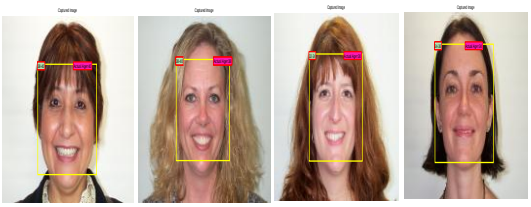
}

end

V. RESULTS & DISCUSSION

In our proposed work we have considered the FG-Net age data base of male and female. The FG-NET aging database is publically available. It contains 1,002 high-resolution color or grey scale face images of 82 multiple-face subjects with large variation of lighting, pose, and expression. Proposed work has been implemented in MATLAB 2013a as its computer vision and image processing toolbox provides a wide range of inbuilt functions

which eased our work's simulation. For example the complex adaboost algorithm used in the first step of face detection is provided in the computer vision toolbox of MATLAB as a function which is used in our work. It provides the option to detect the face area or any part like eyes, nose etc.



The calculated age range and actual image is shown in boxes on the top of images.

After detection of face area, features using the gabor filter are extracted. The accuracy of result is determined by the means square. error, as we are aware with the actual age of subject in the image. The data base named the image such as 'EJWfemale42happy', in which 42 is the age of subject in the particular image. Results are compared with the Nguyen et.al (2014) and presented in table 5.1 below. Like the reference paper we have also taken the male and female images and age has been calculated for that.

Description	Using MLBP Only	Nguyen, D.T. (ref)	Proposed
Female Data	6.816	6.699	2.7
Male Data	5.796	5.783	3.2

Table 5.1: Mean Square Error for comparison with the reference

VI. CONCLUSION & FUTURE WORK

We have developed a fully automatic age estimation framework in this paper. A three modeled architecture is proposed: 1) face detection module; 2) Enhancement module; and 3) classification module. In face detection module, we have built the main components of our human age estimation system. We introduced a face representation schema to crop the face image to the area that covers the face boundary. We have used modified Viola-Jones (adaboost) algorithm. Then, we presented a face feature extraction with new set of Gabor parts (I – Imaginary and M – Magnitude) to extract the aging information. After that, we proposed a unsupervised classification technique for the age estimation task. Our method outperformed the recently applied approaches and algorithms using FG-NET aging datasets.

The evaluation of proposed method is done using mean square error and compared with Nguyen et.al (2014) work. The mean square error difference in proposed work and reference work for male and female data is upto 2.7 and 3.2, which is quite a good achievement.

In light of the good results obtained by applying the feature selection method on age recognition problems, it follows that similar efforts can be employed to improve face recognition problem. Thus, instead of using a single visual descriptor, a possible solution would be to apply feature selection scheme on different regions of the face image.

VII. ACKNOWLEDGEMENT

My sincere thanks go to Mr. Rakesh Dhiman coordinator M.tech Dissertation Evaluation Committee & Mr. Kuldeep Sharma, Head of Electronics & Communication Engineering Department for his help, inspiration and moral support throughout this work. I am grateful to other member of M.Tech Dissertation Evaluation Committee, for giving valuable suggestion and advice while evaluating our work time to time.

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