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Human Age Manifold Learning scheme and Curve Fitting for aging features

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***Abstract* - The focus of this paper is to estimate the human age automatically via facial image analysis. Age estimation is a type of soft biometrics that provides ancillary information of the users' identity information. It can be used to complement the primary biometric features, such as face, fingerprint, iris, and hand geometry, to improve the performance of a primary (hard) biometrics system. Derived from rapid advances in computer graphics and machine vision, computer-based age synthesis and estimation via faces have become particularly prevalent topics recently because of their explosively emerging real-world applications, such as forensic art, electronic customer relationship management, security control and surveillance monitoring, biometrics, entertainment, and cosmetology. Human faces undergo considerable amount of variations with aging. The Human aging pattern is determined by not only the person's gene, but also by many external factors, such as health, living and weather conditions. Males and females also age differently. Hence, it is a challenging problem for the existing computer vision systems to automatically and effectively estimate human ages.**

In our system we introduce the age manifold learning scheme for extracting face aging features and design a curve fitting and regression method for learning and prediction of human ages. The novel approach improves the age estimation accuracy significantly over all previous methods. Benefits of this proposed approaches for image-based age estimation is shown by extensive experiments on a large internal age database and the public available FG-NET database.

***Keywords* – Face Detection, Face Normalization, Robust Regression, manifold learning,.**

I. INTRODUCTION

Face images convey a significant amount of information including information about the identity, emotional state, ethnic origin, gender, age, and head orientation of a person shown in a face image. The human face conveys important perceptible information related to individual traits. The human traits displayed by facial attributes, such as personal identity, facial expression, gender, age, ethnic origin, and pose, have attracted much attention in the last several decades from both industry and academia since face image processing techniques yield extensive applications in graphics and computer vision fields.

This type of information plays a significant role during face-to-face communication between humans. The use of facial information during interaction is made possible by the remarkable ability of humans to accurately recognize and interpret faces and facial gestures in real time. Current trends in information technology dictate the improvement of the interaction between humans and machines, in an attempt to upgrade the accessibility of computer systems. As part of this effort, many researchers have been working in the area of automatic interpretation of face images so that contact-less human–computer interaction (HCI) [1] based on facial gestures can be developed. In this context, systems capable of identifying faces, recognizing emotions, gender, and head orientation have been developed. Despite the fact that the age of a person plays an important role during interaction, so far no researcher has been involved in designing automatic age estimation systems based on face images. With our work, we aim to produce a system which is capable for estimating the age of a person as reliably as humans.

II. MOTIVATION

The motivation behind our work lies in the important real life applications of the proposed methodology. In summary, those applications include the following.

***Age specific human computer interaction*:** If computers could determine the age of the user, both the computing environment and the type of interaction could be adjusted according to the age of the user [9]. Apart from standard HCI, such a system could be used in combination with secure internet access control in order to ensure that under-aged persons are not granted access to internet pages with unsuitable material. A vending machine, secured by the ASHCI system, can refuse to sell alcohol or cigarettes to the underage people. In image and video retrieval, users could retrieve their photographs or videos by specifying a required age range. Ad-agency can find out what kind of scroll advertisements can attract the passengers (potential customers) in what age ranges using a latent computer vision system.

***Age-based indexing of face images*:** Automatic age estimation can be used for age-based retrieval of face images from databases. The most common application of this technology is in e-photo albums, where users could have the ability to retrieve their photographs by specifying a required age-range.

***Development of automatic age progression systems*:** Automatic age estimation systems rely on their ability to understand and classify changes in facial appearance due to aging. The methodology required in this task could form the basis of designing automatic age progression systems (i.e., systems with the ability to predict the future facial appearance of subjects). A description of our early work in this area is described elsewhere.

***Understanding the process of age perception by humans*:** Work in the area of automatic age estimation could provide invaluable help to psychologists who study the topic of age perception by humans.

III. RELATED WORK

Automatic image-based human age estimation is an important technique involved in many real-world applications. Estimating human age automatically via facial image analysis has lots of potential real-world applications, it is still a challenging problem to estimate human ages from face images since different individual's age quite differently. The aging process is determined by not only the person's gene, but also many external factors, such as health, living style, living location and weather conditions.

The current age estimation performance is still not good enough for practical use and more effort has to be put into this research direction. The biases in **Age estimation** in many cases are not constant across subgroups of a population.

There are three important methods that can categorize most existing image-based human age estimation technique [7].

- ***Anthropometric Model***
- ***Aging Pattern Subspace***
- ***Age Regression***

A. Anthropometric Model

The cranio-facial development theory and facial skin wrinkle analysis are used to create the anthropometric model [1]. The changes of face shape and texture patterns related to growth are measured to categorize a face into several age groups. These methods are suitable for coarse age estimation or modeling ages just for ***young people*** [7]. However, they are not designed for continuous or refined age classification.

B. Aging Pattern Subspace

To handle highly incomplete data due to the difficulty in data collection, Aging pattern Subspace models [4] a sequence of personal aging face images by learning a subspace. The age of a test face is determined by the projection in the subspace that can best reconstruct the face image. These kinds of methods are designed to deal with the difficulty of utilizing the ***incomplete age databases***.

C. Age Regression

For the regression methods, facial features are extracted by the active appearance models (AAMs) [3] that incorporate the shape and appearance information together. An input face image is then represented by a set of fitted model parameters. The regression coefficients are estimated from the training data with an ***assumption*** of the regression function such as a quadratic model.

IV.PROPOSED SYSTEM

In our paper, refined age estimation technique by age manifold analysis is implemented

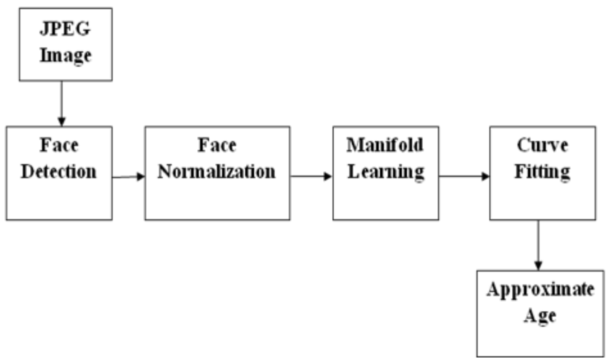

Fig. 1 Age Estimation Process

The age manifold analysis [8] has two advantages to facilitate the age estimation task. First, the manifold analysis is a way to represent the original age data in low dimensionality which is necessary to overcome lack-of-fit of the regression model. Second, the manifold learning captures the underlying face aging structure which is important for accurate modeling and age prediction. Regression gives an efficient methodology for mapping the low dimensionality manifold data into accurate age values.

A. Face Detection

1) ***Color Models*:** Different color spaces used in skin detection previously include HSV, normalized RGB, YCrCb, YIQ and CIELAB [10].HSV gives the best performance for skin pixel detection. We conducted our own experiments independently and converged to the same fact. The experiments also showed the superiority of HSV color space over RGB and YCrCb color spaces [11]. In the HSV space, H stands for hue component, which describes the shade of the color, S stands for saturation component, which describes how pure the hue (color) is while V stands for value component, which describes the brightness. The removal of V component takes care of varying lighting conditions. H varies from 0 to 1 on a circular scale i.e. the colors represented by H=0 and H=1 are the same. S varies from 0 to 1, 1 representing 100 percent purity of the color and S scales.

2) ***Connectivity Analysis:*** Group the skin pixels in the image based on an 8-connected neighborhood i.e. [11] if a skin pixel has got another skin pixel in any of its 8 neighboring places, then both the pixels belongs to the same region. At this stage, we have different regions and we have to classify each of these regions as a human face or not. This is done by finding the centroid, height and width of the region as well as the percentage of skin in the rectangular area defined by the above parameters. The centroid is found by the average of the coordinates of all the pixels in that region. For finding height, the y-coordinate of the centroid is subtracted from the y-coordinates of all pixels in the region. Find the average of all the positive y-coordinates and negative y-coordinates separately. Add the absolute values of both the averages and multiply by 2 [11]. This gives the average height of the region. Average width can be found similarly by using x co-ordinates. Since the height to width ratio of human faces falls within a small range on the real axis, using this parameter along with percentage of skin in a region, the algorithm should be able to throw away most of non face skin regions. So if the height to width ratio falls within the range of well known golden ratio tolerance and if the percentage of skin is higher than a threshold called percentage threshold, then that region is considered a face region. The algorithm works with faces of all sizes and does not assume anything about the scale at which a face appears.

3) Proposed Algorithm

Input: JPEG Image containing Face image.

Step 1: Convert the input RGB image(rgb(i,j)) into HSV image(hsv(i,j)).

Step 2: Get the edge map image (edge(i,j)) from RGB image using Sobel operator.

Step 3: For each pixel (i,j), get the corresponding H,S values.

Step 4: If (colorhistogram(H,S) ϵ Skin Range) and edge(i,j) < edge threshold)
then skin(i,j)=1 i.e. (i,j) is a skin pixel.
else skin(i,j)=0 i.e. (i,j) is a non-skin pixel.
where Skin Range are threshold values

Step 5: Find the difference regions in the image by implementing connectivity analysis using 8-connected neighborhood.

Step 6: Find height and width for each region and percentage of skin in each region.

Step 7: For each region, if (height/width) or (width/height) is within the range and (percentage of skin > threshold value)
then the region is a face,
else it is not a face.

Output: Rectangular cropped face patch.

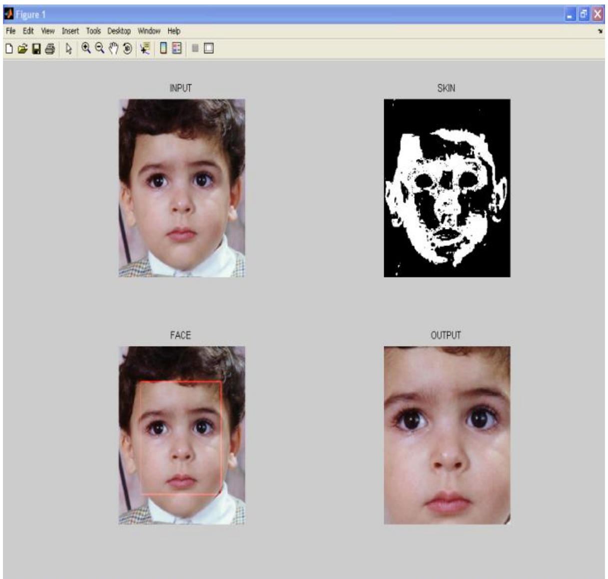

Fig. 2 Face Detection

B. Face Normalization

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast without affecting the global contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

1) Proposed Algorithm

Input: Rectangular cropped face patch.

Step 1: Convert the facial detected image into a uniform size.

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Step 2: Apply illumination normalization to the resized image through Histogram equalization.

$cdf(v) = round((cdf(v) - cdf_{min})* (L-1)/(M*N) - cdf_{min}))$
L = number of gray levels used.
M=width.
N=height.

Output: Normalized face image.

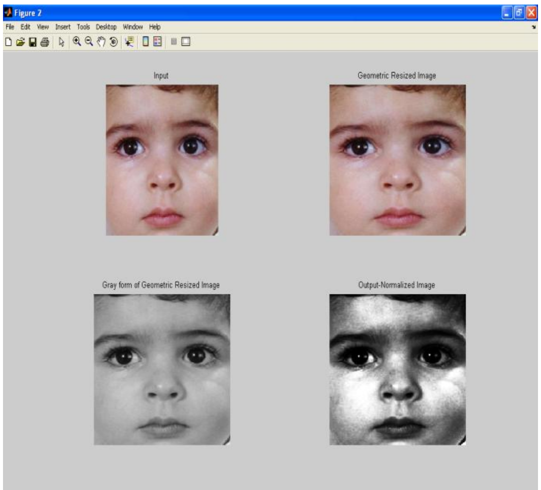

Fig. 3 Face Normalization

C. *Manifold Learning*

Age is one of the basic attributes in facial images. The objective of manifold embedding is to find a matrix satisfying or directly find n ×d matrix P satisfying $Y=P^TX$, or directly find Y, where Y= {y1, y2,…., yn},X={x1,x2,…..,xn}and P={p1,p2,…. .pn} In a supervised manner, manifold embedding constrains to search nearest neighbors.

Some typical dimensionality reduction and manifold embedding methods are as follows: Principal Component Analysis (PCA), Locally Linear Embedding (LLE) [8] and Orthogonal Locality Preserving Projections (OLPP) [6].

The Locality Preserving Projection (LPP) algorithm, which aims at finding a linear approximation to the eigen functions of the Laplace Beltrami operator on the face manifold. However, LPP is non-orthogonal, and this makes it difficult to reconstruct the data. The orthogonal locality preserving projection (OLPP) method produces orthogonal basis functions and can have more locality preserving power than LPP. The LPP searches the embedding that preserves essential manifold structure by measuring the local neighborhood distance information. The OLPP is expected to have more discriminating power than LPP.

1) Proposed Algorithm

Input: Normalized face image

Step 1: Find the feature points using hough transform
Step 2: Apply OLPP to measure the neighbourhood distance information by graycomatrix function
Step3: Study the = {args various measures and determine a suitable
$P\ (\min\sum_{i=1}^{n} \sum_{j=1}^{n} (P^Tx_i-P^Tx_j)^2 * S_{i,j})\}$
P=optimal Laplace Projection.

Output: Feature Pattern for Regression.

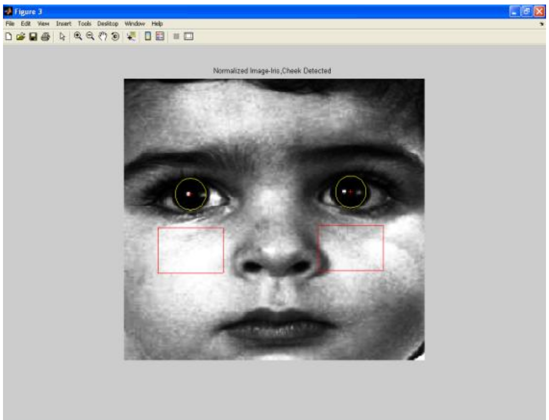

Fig. 4 Manifold Learning

D. *Curve Fitting*

Curve fitting is finding a curve which has the best fit to a series of data points and possibly other constraints. This section is an introduction to both interpolation (where an exact fit to constraints is expected) and regression analysis. Both are sometimes used for extrapolation. Regression analysis allows for an approximate fit by minimizing the difference between the data points and the curve. Robust regression is also efficiently done using curve fitting.

Regression analysis is the statistical term for curve fitting. We produce a curve that best fits some observed data points. Using regression, we can make predictions as to the behavior of some property in the future. Curve fitting can be performed for any degree, and matlab offers two simple functions for this purpose.

Using function ***polyfit,*** we pass parameters for the range of data(x), the actual values(y), and the degree of the polynomial to which the data is to be fit. Polyfit returns a vector with (DEGREE + 1) elements, corresponding to the polynomial coefficients, starting with the highest degree.

Using ***polyval,*** the vector of coefficients can be evaluated for any data range of X. polyval takes as input parameters a vector of coefficients, and the data range over which a corresponding Y vector is to be performed.

1) Proposed Algorithm

Input: Feature Pattern

Step 1: Find the appropriate polynomial that fits the feature pattern and age details.

Step 2: Map the polynomial into regressive curve.

Regression function:

Age Label L=f(y), where y=manifold data.

The training phase includes all the above processes. During test, an input face image undergoes face detection, Normalization etc except the feature pattern generation (Polynomial fitting).

Output: Appropriate age for the subject in the image is determined.

V. IMPLEMENTATION METHODOLOGY

Our proposed system gets a jpeg image as input. The rectangular facial region is detected from the input image.

First color model threshold analysis is used to find whether a pixel is a skin pixel or not. Then connectivity analysis is applied to find the facial region which is a group of skin pixels that forms the face. Now draw a rectangle over the facial region and it is cropped separately into a variable.

Now the cropped image is resized into uniform assumed size. Then Apply histogram equalization to perform illumination normalization. Now get a normalized face image in which we will perform the Manifold Learning. Next do the ground work for manifold learning i.e. feature point detection by applying Hough transform on the normalized image. Perform Manifold learning (OLPP) by measuring the local neighborhood distance information such as contrast, correlation, homogeneity, entropy etc., These values can be calculated from the gray comatrix of the region(cheek, forehead) chosen for age estimation. Thus our focus shifted from a higher dimension data to lower dimension data. Now find the trend between the features determined and age labels using Regression (curve fitting). This can be done by the curve fitting toolbox present in matlab.

A large number of training images are collected from a broad range of subject ages. The cropped face patches undergo a normalization including illumination normalization (basically histogram equalization). Then the age manifold is learned to map the original face image data into a low-dimensional subspace. A regression function is applied to fit the manifold data.

For test, an input face picture goes through the same process of face detection and normalization. Then the normalized face image is projected on the learned manifold which was computed in the learning stage. Finally, the discrete classification of the age of the input face image is done and an approximate age is found out.

VI. CONCLUSION

The proposed system is tested with FGNET database images which contain only a single face. This is done only in order to preserve the local neighborhood information that helps in determining the feature that varies with ages. The current system first discretely classifies the subject in the image and then estimates the approximate age of the person close to the age mentioned in the database and suggests a range within which the age of the person might be.

REFERENCES

[1] Guodong Guo, Yun Fu, Charles R. Dyer and Thomas S. Huang, "Image based human age estimation by manifold learning and locally adjusted robust regression", IEEE Trans. Image processing, vol. 17,No. 7, July 2008.

[2] The FG-NET Aging Database Available: http://www.fgnet.rsunit.com/

[3] Y. Fu and T. S. Huang, "Human age estimation with regression on discriminative aging manifold," IEEE Trans. Multimedia, to be published..

[4] X. Geng, Z.-H. Zhou, Y. Zhang, G. Li, and H. Dai, "Learning from facial aging patterns for automatic age estimation," in Proc. ACMConf. Multimedia, 2006, pp. 307–316.

[5] Y. Fu, Y. Xu, and T. S. Huang, "Estimating human ages by manifold analysis of face pictures and regression on aging features," in Proc. IEEE Conf. Multimedia Expo., 2007, pp. 1383–1386

[6] D. Cai, X. He, J. Han, and H.-J. Zhang, "Orthogonal laplacianfaces for face recognition," *IEEE Trans. Image Process.*, vol. 15, no. 11, pp.3608–3614, Nov. 2006.

[7] N. Ramanathan and R. Chellappa, "Modeling age progression in young faces," in *Proc. IEEE Conf. CVPR*, 2006, pp. 387–394.

[8] S. T. Roweis and L. K. Saul, "Nonlinear dimensionality reduction by locally linear embedding," *Science*, vol. 290, pp. 2323–2326, 2000.

[9] A. Lanitis, C. Draganova, and C. Christodoulou, "Comparing different classifiers for automatic age estimation," *IEEE Trans. Syst., Man, Cybern.B, Cybern.*, vol. 34, no. 1, pp. 621–628, Feb. 2004.

[10] Sanjay Kr. Singh, D.S. Chauhan, Mayank Vatsa, Richa Singh, "A Robust Skin Color Based Face Detection Algorithm," Tamkang Journal of Science and Engineering, Vol.6, No. 4, pp. 227-234 (2003).

[11] K. Sandeep and A.N. Rajagopalan, "Human Face Detection in Cluttered Color Images Using Skin Color and Edge Information".