AGE CLASSIFICATION: BASED ON WRINKLE ANALYSIS

M.Z.Lazarus, K.Srilakshmi and Sandeep V.M
Jaya Prakash Narayan College of Engineering, Mahabubnagar,
Andhra Pradesh, India – 509001
zefree.lazarus@gmail.com, siri460@gmail.com, svmandr@yahoo.com

ABSTRACT: **As humans, we are capable to categorize a person's age group from an image of the person's face. This ability has not been pursued in the computer vision community. The method proposed in this article is capable of segregating the given input images into three clusters namely: Baby; Adult; Senior. The computations are based on wrinkle analysis algorithms.**

KEYWORDS: **Age Classification, Wrinkles.**

*****

INTRODUCTION

Face is a prolific information source. People can effortlessly extract many kinds of useful information from a face image, such as identity, expression, emotion, gaze, gender, age, *etc*. The automatic extraction of most of the information has been extensively studied in several research areas including multimedia, HCI, computer vision, pattern recognition, machine learning and neural networks.

People at different ages have different requirements and preferences in various aspects, such as linguistics, aesthetics and consumption habit. Consequently Age Specific Human-Computer Interaction (ASHCI) is widely demanded by numerous applications in daily life. With ASHCI, for example, an enquiry terminal can automatically choose the vocabulary, interface, and services that suit the customer's age; A web browser can determine by itself whether the user satisfies the age limitation to view certain web pages; A vending machine will refuse to sell alcohol or cigarettes to the underage people.

In order to begin researching the issues involved in this process, this paper addresses the limited task of age classification of a mug-shot facial image into a baby, young adult, and senior adult [2],[4].

From studying the aging process of adult humans, one can observe that the facial skin of an older person is not as taut as in a younger adult. Wrinkles are a good indication of the loosening skin; thus we have selected wrinkles as the next important feature (although, in general, these aging-wrinkles must not be confused with creases formed from facial expressions).

PRIOR WORK ON AGE CLASSIFICATION

The specific challenges with age classification are that the age of the person is hard to predict exactly because facial appearance changes slowly when a person is aging and this change in appearance is somewhat person dependent. Further, bone structure and wrinkles are also affected by other factors than age alone. For example, identity and ethnicity affect the bone structure and wrinkles that appear within aging can also be caused by facial expressions.

Kwon and Lobo (1999) used facial feature detection and wrinkle detection to classify age to the three age groups: babies, young adults and seniors. They carried out experiments with the faces of 5 babies, 5 young adults, and 5 seniors. Using the locations between detected facial features and the number of wrinkles on the face they determined the age group of the face. Classification was successful for all 15 faces. Ueki et al. (2006) presented a classifier based on two phases using 2D-LDA and LDA to classify age. The benefit of their classifier is that it is robust under various lighting conditions. Ueki et al. (2006) experimented by using age ranges of 5 years, 10 years, and 15 years. The respective classification rates for each range were 46.3%, 67.8%, and 78.1%. Besides classification to age groups it is also possible to estimate the exact age of the person. The studies by Lanitis (2002) and by Lanitis et al. (2004) achieved roughly a 5-year mean error in the experiments where they used face images of people aged between 0 and 35 years. In the recent past many such classification strategies have been developed [1], [3].

The major setback in this area is that collection of facial images of the same person at different age groups are hard to get. Also the wrinkle geometry extraction techniques are complicated and have been evolved very recently. Lately database, specifically intended for research on face based age classification: FG-NET Aging database (FG-NET, 2007) has been available.

The difficulty in automatic age estimation is mainly due to the specialty of aging effects on the face compared with other facial variations. The unique characteristics of aging variation mainly include:
1. *The aging progress is uncontrollable.* Sad but true, no one can age at will. The procedure of aging is slow and irreversible. Thus the collection of sufficient training data for age estimation is extremely laborious.
2. *Personalized aging patterns.* Different persons age in different ways. The aging pattern of each person is determined by his/her gene as well as many external factors, such as health, living style and weather conditions, *etc*.

3. *The aging patterns are temporal data.* The aging progress must obey the order of time. The face status at a particular age will affect all older faces, but will not affect those younger ones.

For accurate age estimation, the aging feature extraction is very important since the extracted features highly affect to the performance of age estimation. For this reason, there have been many efforts for extracting discriminative aging features. The features used for age estimation are divided into two features [6]. They are:

1. Global features
2. Local features

Global features

As global features, there are Active Appearance Models (AAM), Gabor wavelet transform (GWT), subspace features using intensity of images and so on. Among them, AAM is mainly used to estimate age by many researchers because AAM is a face modeling method which includes both appearance and shape; it offers sufficient information for detailed age estimation. The first age estimation algorithm using AAM features was proposed by Lanitis. In his work, the relationship between age and features was defined by quadratic aging functions, and then facial age was estimated by aging features. After that, Lanitis used AAM features for comparing different classifiers for age estimation.

Xin Geng proposed aging pattern subspace – AGing pattErn Subspace (AGES) using subspace representation of a sequence of individual aging face images. Yan designed regressor based on training samples with uncertain nonnegative labels by using AAM features. Though AAM is frequently used in previous works, AAM features have a problem that they do not contain enough information about local features such as wrinkle and skin because of dimensional reduction by PCA.

Problems of using Global features

1. There are large shape and texture variations over a long period, say 20-50 years: hair whitens, muscles drop, wrinkles appear, and so on. In the traditional AAM model [11] it is hard to describe all of these variations.
2. The perceived face age often depends on global non-facial factors, such as the hair color and style, the boldness of the forehead, etc., while these non-facial features are usually excluded in face aging modeling.
3. It is very difficult to collect face images of the same person over a long time period and the age-related variations are often mixed with other variations (i.e, illumination, expression, etc.).
4. There exist large variations of perceived age within each biologic face group due to external factors, such as health, life style, etc.
5. There is a lack of quantitative measurements for evaluating the aging results in the literature.

Local features

Therefore, local features are required to improve the performance. As local features, wrinkle and skin features were frequently used in many previous works. The wrinkle and skin features are generally appeared by high frequency components on face images. Therefore, edge detector or high frequency images are used to extract local features. Takimoto used sobel filter and difference image between original and smoothed images to extract wrinkle and skin features. Jun-Da Xia and Chung-Lin Huang proposed age classification method by using wrinkle features extracted by sobel filter and hair color features. The regions for feature extraction were selected based on facial landmark detected by AAM. In these previous methods, local features were mostly used for age group classification because local features indicate the characteristics of age group rather than entire range of age. In order to improve the performance of age estimation, the research about detailed age estimation using local features and comparison of various local features extraction methods are required. Of which, the Horng classification of age group by using density and depth of wrinkle, average variance of canny filtered images is employed in this paper.

IMPLEMENTAION:

HOUGH TRANSFORM TECHNIQUE

Algorithm for detecting lines (wrinkles) in images. The steps are as follows:

1. Find all the edge points in the image using any suitable edge detection scheme.
2. Quantize the (m, c) space into a two-dimensional matrix H with appropriate quantization levels.
3. Initialize the matrix H to zero.
4. Each element of H matrix, $H\,(m_i,c_i)$, which is found to correspond to an edge point is incremented by 1. The result is a histogram or a vote matrix showing the frequency of edge points corresponding to certain (m, c) values (i.e. points lying on a common line).
5. The histogram H is thresholded where only the large valued elements are taken. These elements correspond to lines in the original image.

Advantages and Disadvantages

The advantage of the Hough transform is that the pixels lying on one line need not all be contiguous. This can be very useful when trying to detect lines with short breaks in them due to noise, or when objects are partially occluded.
As for the disadvantages of the Hough transform, one is that it can give misleading results when objects happen to be aligned by chance. This clearly shows another disadvantage which is that the detected lines are infinite lines described by their (m,c) values, rather than finite lines with defined end points.

A database of many facial images of different age groups is taken. Of which, to start with, small portions of skin regions (cropped portions) are extracted from facial images and another database is created. The database consists of images of three kinds as -

1. Image with dominant wrinkles / Aged person.
2. Image with average number of wrinkles / Middle aged person.
3. Image with less or no wrinkles / Baby / Young person.

Later the images are given numbers randomly. Each image is read individually by using MATLAB. For applying edge detection technique on the input images, there are certain preprocessing steps to be followed.
They are:

1. The input image (suppose a color image) is converted into grayscale image, as it is necessary to do so for applying edge detection technique.
2. The size of the image (m*n) should be noted as it plays a vital role in calculating normalized values.

Suppose a situation where the input image consists of only one large sized wrinkle or a scar. If we take the peak value or number of edge points as key constraint then, on applying the transform it will be deduced that the input image is of an old person. But generally wrinkles appear in a group and are distributed around a specific region. That is there will be many number of peak values, and each peak value would constitute to the number of edge points. So, accuracy of the program can be improved greatly if we consider normalized values.
As in any given input facial image, there will be many peak values of very wide ranges (very small to very large). Of all the wrinkles (lines) detected we are concerned with wrinkles which make a mark on the skin. That is very small wrinkles are neglected. So we prefer to take into consideration only those wrinkles which are significant on the face. This filtering of small lines (wrinkles) is called Thresholding.
In this procedure two new constraints are taken into consideration.

1. Normalized peak value.
2. Normalized value of number of edge points.

Mathematical definition of the key constraints:

1. Peak value (MAX): There are many peak values in the accumulator array. By applying threshold smaller peaks are eliminated. Later the array with maximum value of the votes is taken as peak value.
2. Normalized peak values: The above value is divided by the total number of pixels present in the image (m*n), which gives us normalized peak value.
   This is given by (MAX) / (m*n).
3. Number of edge points (TEP): After edge detection technique is employed, the HT is performed on each edge value. All such points constitute the Number of edge points.

Input image

This is a cropped image of skin region near the cheeks. Its dimensions are (256*256).
Later Canny edge detection is employed. A threshold of 10 is used. The above figure gives us the edges detected. For every detected edge point the transform is performed. On doing so we get the values of total number of edge points say TEP. Among these the maximum peak value is taken say MAX. Once the values of TEP & MAX are known, normalized values are got by dividing them by total number of pixels (m*n).

The same is done with the 10 figures shown in the tabular form below:

S.No	Figure	Peak {MAX}	Normalized Peak ={MAX/(m*n)}	No of edge pt	Normalized Value ={TEP/(m*n)}
1		20	0.005	179	0.0448
2		23	0.0058	41	0.0103
3		23	0.0058	117	0.0293
4		38	0.0095	181	0.0453
5		9	0.0023	16	0.004
6		13	0..033	107	0.0268
7		20	0.005	91	0.0228
8		10	0.0025	18	0.0045
9		29	0.0073	202	0.0505
10		12	0.003	20	0.005

Table I: *Normalized peak & Number of edge points for various skin structures*

Inference from the above table

The table gives us the statistical data of the Kind of image taken, its peak value, Number of edge points and normalized values. Form the table it is clear that:

- Image with large number of wrinkles has a more Number of edge points.
- We can not take the Peak value as key constraint.
- There are three regions in which the Total number of edge points can be classified into:

a. Small TEP values : 0 to 20
b. Medium TEP values : 21 to 107
c. Large TEP values : 108 to 202

- The Normalized values give us even a better picture.

The above experiment adds to the following statement

Age of the person ∝ Number of edge points detected.

Similarly, the above calculations are performed on a database of 500 such images. The individual Peak values and the total number of Edge points are tabulated.

On observing the results, the treshold values have been fixed. With the help of the threshold values we can differentiate the images into three classifiactions :

1. Image with less number of wrinkles
2. Image with more number of wrinkles
3. Image without wrinkles

Threshold Values of normalized edge points:

For images with more wrinkles : Value > 0.035932

For images with less wrinkles : 0.019 < Value < 0.0359

For images without wrinkles : 0.019042857 > Value

On applying the threshold values, the above test images in the table are classified as

S.No	Classification type	General Type	Figure No
1	More wrinkles	Old aged person	1,3,4,9
2	Less wrinkles	Middle aged person	2,6,7
3	No wrinkles	Young / Baby	5,8,10

Table II: *Classification based on normalized peak and edge point values*

Limitations of the above discussed method

1. While using the above technique, the classification is not accurate.

   For example: If an image contains any big scar, then the algorithm will show a large Peak value. In such cases there is a chance of misconseption. In order to over come this, a new parameter is employed.
2. The time required for computing the results are also pretty high.

So a simple and more efficient method II is employed.

METHOD II:

IMPLEMENTATION BY USING WRINKLE DENSITY, DEPTH AND AVERAGE SKIN VARIANCE AS CONSTRAINTS

The wrinkles emerge and become more pronounced when skin changes with age. The wrinkles can provide some indications of the age of a person. Aged people have clear wrinkles on the areas forehead, eye corners and cheeks of a face. Digital images are captured and MATLAB codes are used for the following purposes:

i) Preprocessing,
ii) Cropping of Forehead, Eye Corner and Cheek and
iii) Feature Extraction.

The process of the system is mainly composed of three phases – location, feature extraction and age classification.

Preprocessing

In preprocessing, the color image is converted to HSV model and histogram equalization is done.

Constraints Defined

i) Wrinkle Density

The density of wrinkles in area *A* is defined as ***D*** *(*1, *A)* = │Wa│/ │Pa│where │Wa│is the number of wrinkle pixels in area *A* and │Pa│is the number of pixels in *A*.

ii) Wrinkle Depth.

The depth of wrinkles in area *A* is defined as ***D (***2, *A)* = $\sum M(g(x,y))/\alpha|Wa|$ where *M* (*g* (*x*, *y*)) is the canny edge magnitude of wrinkle pixel with coordinates (*x*, *y*) in *WA* and $\alpha = 255$.

iii) Average Skin Variance.

The average skin variance in area *A* is defined as ***D*** *(*3, *A)* = $\sum M(g(x,y))/\alpha|Pa|$ where *M*(*g*(*x*, *y*)) is the canny edge magnitude of pixels with coordinates (*x*,*y*) in *PA* and α =255. The above three wrinkle features are extracted in each of three areas.

When wrinkle areas are extracted, an edge detector is used to measure the density of wrinkles. This density is used for adults to estimate their age groups. Due to the variance of gray levels, wrinkles have obvious changes in intensity and some even appear clear lines. From this aspect, if a pixel belongs to an edge it is labeled as a wrinkle pixel. The edge detector is utilized to find wrinkles. It is important that edges on images should not be missed or mistaken. In the proposed method, it takes the saturated image ''I'' as the input, and returns a binary image with the same size. The function returns 1 when it finds wrinkles in the input image and returns 0 elsewhere. Then wrinkle density in area ''I'' is calculated.

To compare the degree of the skin creases of young adults with the elderly, wrinkle density related to their forehead region is calculated as a sample in Figure. Wrinkle areas like other facial feature perimeters are very relevant to the anthropometric properties of the face, especially distances between the eyes [5], [8].

Consider the following set of pictures as sample to verify the above algorithm. We get:

Reading Image

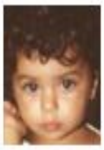
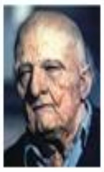
Nature of Image	Figure 1	Figure 2	Figure 3	Figure 4	Figure 5
Type 1					
Type 2					
Type 3					

Table III: Sample pictures of different aged grouped images in the database taken.

Here three types of images are taken into account. The Type–I images consists of facial images of babies. Type-II consists of Middle aged persons. Type-III is a complilation of Aged people facial images. The images are arranged in three different rows as shown above. The above images are read individually and by employing the Mouse input fuction, portions of skin are extracted for the analysis purpose.

RESULTS:

A large database of 300 facial images is taken (100 for each category) and the following steps are repeated:

1. Read image.
2. Convert it into HSV model.
3. Perform Histogram equilization on the Saturated image.
4. Take the mouse input & select wrinkle portion.
5. Apply Canny Edge detection technique.
6. Calculate Wrinkle Density.
7. Calculate Wrinkle Depth.
8. Calculate skin variance.
9. Apply thresholds.

A table is created with the values of the constraints for the whole database of images.

Thresholds Values

Nature of image	Number Of Subject Elements	Wrinkle Densities	Wrinkle Depths	Wrinkle Skin Variance
Babies	100	0.069	0.058	0.00408
Middle Aged	100	0.18	0.1344	0.02478
Seniors	100	0.78	0.1473	0.11962

Table IV: *Average values of the three parameters.*

On employing the above threshold values one can easily differentiate all the images of a given database.

Subject_Image No	Density	Depth	Skin Variance	Decide Wrinkled?	Computed lable
Baby_20	0.0453	0.0125	0.00102	No	Baby
Baby_40	0.0512	0.0541	0.00208	No	Baby
Baby_60	0.0478	0.0425	0.00314	No	Baby
Baby_80	0.0624	0.0424	0.00129	No	Baby
Baby_100	0.0294	0.0245	0.00287	No	Baby
Middle age_20	0.1799	0.0678	0.00842	No	Middle age
Middle age_40	0.1802	0.0784	0.01427	No	Middle age
Middle age_60	0.0978	0.0915	0.00924	No	Middle age
Middle age_80	0.1578	0.1247	0.02202	No	Middle age
Middle age_100	0.1259	0.7594	0.02145	No	Middle age
Seniors_20	0.2457	0.1345	0.04865	Yes	Seniors
Seniors_40	0.4265	0.1460	0.08455	Yes	Seniors
Seniors_60	0.4859	0.1478	0.10556	Yes	Seniors
Seniors_80	0.6887	0.1395	0.09454	Yes	Seniors
Seniors_100	0.7458	0.1420	0.10866	Yes	Seniors

Table V: *Sample of final image classification table*

This a more easier and fast way to classify images. The overall accuracy of these resluts in 100 %. Thus the given input facial image can be classifed.

CONCLUSION & FUTURE SCOPE

Human aging is an important aspect for biometrics and also for all face processing applications and not studied in depth yet. The studies on this field may yield some insight for the Age Conception in human beings. Collecting database is not easy but fortunately, there are various sources to start with. The subject has various aspects and various impacts on different disciplines. For example, aging is an obstacle in face recognition (beside others such as beard, glasses etc.). On the other hand, aging is a natural process in humans' life and there might be thousands of computer vision applications regarding this process. Age estimation is one of the major issues in those applications. Another one is modeling the aging process. This latter may be useful in security applications (such as in passport control), or finding lost children.

The bottom line is: “Aging” is an important aspect that has various impacts on different disciplines and a fertile ground for future research.

REFERENCES

[1] Y. Bando, T. Kuratate, and T. Nishita, “A Simple Method for Modeling Wrinkles on Human Skin,” Proc. 10th Pacific Conf.
Computer Graphics and Applications, pp. 166-175, 2002.

[2] Y. Wu and N.M. Thalmann, “A Dynamic Wrinkle Model in Facial Animation and Skin Aging,” J. Visualization and Computer Animation, vol. 6, pp. 195-205, Oct. 1995.

[3] Wen-Bing Horng, Cheng-Ping Lee and Chun-Wen Chen, “Classification of Age Groups Based on Facial Features”, Tamkang Journal of Science and Engineering, vol.4, no.3, (2001), pp.183- 192.

[4] Kwon, Y. H. and da Vitoria Lobo, N.,“Age classification from facial images,” *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, Seattle, Washington, U. S. A., pp. 762-767 (1994).

[5] Xin Geng, Zhi-Hua Zhou, Yu Zhang, Gang Li, Honghua Dai, Learning from facial aging patterns for automatic age estimation, Proceedings of the 14th annual ACM international conference on Multimedia, pp. 307-316, 2006.

[6] Rafael C. Gonzalez, Richard E. Woods, Digital image processing, Second Edition.

[7] Young H. Kwon and Niels Da Vitoria Lobo, “Age Classification from Facial Images,” *Journal of Computer Vision and Image Understanding*, vol. 74, no. 1, pp. 1-21, April 1999.

[8] N. Ramanathan and R. Chellappa, “Face Verification Across Age Progression,” *IEEE Trans. on Image Processing*, vol. 15, no. 11, pp. 3349-3361, 2006.

Authors Information:

1. M.Z.Lazarus completed M.Tech(DSCE) from Jaya Prakash Narayan College of Engineering B.Tech(EEE) from University college of Engineering (KU). Currently he is working as Assistant Professor at Jayaprakash Narayan college of engineering And has 4 years of experience in teaching .His areas of interest include Image Processing, FACTS.

2. K.Srilakshmi completed M.Tech(DSCE) from Jaya Prakash Narayan College of Engineering B.Tech(ECE) from Jaya Prakash Narayan College of Engineering. Currently she is working as Assistant Professor at Jayaprakash Narayan College of Engineering and has 4 years of experience in teaching. Her areas of interest include, Image Processing, signal processing, Electronics.

3. Dr. Sandeep V.M. completed Ph.D in Faculty of Electrical and Electronics Engineering Sciences, from Visveswaraiah Technological University, Belgaum, and M.E from Gulbarga University and B.E from Gulbarga University, Currently he is working as Professor at Jayaprakash Narayan College of engineering and has 25 years of Experience in teaching. His research interests are in the areas of Signal and Image Processing, Pattern Recognition, Communication, Electromagnetics. He is Reviewer for Pattern Recognition Letters (PRL). He acted as Reviewer for many International Conferences. He has 24 years of teaching experience. He is member of LMIST – Life Member Instrument Society of India (IISc, Bangalore). And he guided more than 100 projects at UG level, more than 40 at PG level. and has 2 research scholars under his guidance, more than 10 papers in International journals and 9 papers Conference Proceedings.