Comprehensive Review on Facial based Human Age Estimation

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***Abstract* --** Recently facial based age estimation has become increasingly important because of many potential real time applications. Age estimation is predicting someone's age by analyzing his/her biometric trait such as bone density, dental structure or face. Amongst these face is important trait so facial based age estimation has become more popular due to its vast real time applications. Age estimation is defined as to label the face image automatically with the exact age or age group. Estimating age from images has been one of the most challenging problems within the field of facial analysis due to uncontrollable nature of the aging process, high variance of observations within the same age range, lighting, facial expressions, pose, occlusion, blur, camouflage due to beards, moustache, glasses, makeup and the difficulty to gather complete and sufficient training data. This paper presents analysis of earlier techniques proposed by researchers for facial based age estimation. Different feature extraction and estimator learning methods used in this domain are also discussed.

***Keywords* --** Facial aging; age estimation; age progression.

I. INTRODUCTION

Human face convey significant amount of nonverbal information about the person such as identity, age, ethnic group, gender, posture, and expression. Facial age estimation has become an interesting and attractive topic in recent years due to its many real time potential applications, such as surveillance, electronic vending machines, security control, forensic art, entertainment, and cosmetology. As the age progresses, the appearance of human faces shows remarkable changes

People have the ability, developed early in the life to predict age by looking towards face of a person. We expect that machine should also predict age like human do. Recent advances in computer science and engineering has made it possible. Figure 1 shows predicted age for the given image [4].

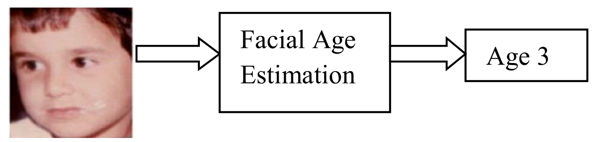

Fig. 1 Labeling face image automatically.

Four concepts about human age are introduced in [2].

Actual Age – This is also called as Chronological age defined as the number of years a person has lived. This is the real age (cumulated years after birth) of an individual.

Appearance Age – Age defined by the person's visual appearance

Perceived Age –Age defined by the other people who define it on the basis of visual appearance.

Estimated Age - Age recognized by the computer based on person's visual appearance

The objective of age estimation is that estimated age should be close to appearance age[3].

Related to this topic, some basic terms are defined. The craniofacial morphology is a study of shape of the face and skull. Changes in face associated with skin and muscle elasticity indicates changes in texture of face. The changes that occur are related to craniofacial morphology and face texture[3].

Geng et al. [4] in their work on the automated age estimation recognized two stages of facial aging. The First phase is the early years, defined as the years from birth to adulthood. At this stage, most of the changes are in craniofacial growth that is shape of the face changes greatly. This includes Chin becomes more prominent, Cheeks are spread over a larger area, Characteristics of face increase, forehead falls back, reduces the free space on the surface of skull. In addition minor changes in skin occur like facial hair become denser and change color, Skin color changes. The second phase of the aging face, recognized by Geng et al. [4] is during adulthood. Adulthood is defined as the time from the end of growth to old age. In this stage important change occurs in the texture of the face. Skin becomes thinner, darker, less elastic and more leathery. Also,

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wrinkles, under chin, sagging cheeks and lowered bags under the eyes appear and minor changes occur in the craniofacial growth.

A. *Organization of the Paper*

The remaining part of the paper is organized as follows: Section 2 describes the motivation behind this topic. Section 3 presents different steps in facial based age estimation process. This also introduces existing face models for representation of image and different estimator learning methods. Section 4 lists some standard facial aging databases and their features used by different researchers. Section 5 describes performance measures used by researchers. Comparison of different methods based on their Mean absolute Error (MAE) is also presented. Section 6 presents challenges that are being faced by automated age estimation systems. Finally conclusion and future scope is discussed.

II. MOTIVATION

There are many popular and potential real world applications where we are mainly concerned in identifying age of the individual.

A. *Age specific human computer interaction* for Security Control

Age plays an important role for human computer interaction**.** If computers could predict the age of the user secure internet access can be provided. For example denying underage persons to access adult web sites with unsuitable material or restricted movies [5], preventing minors from purchasing tobacco products from vending machines.

B. *Surveillance Monitoring*

Security control and surveillance monitoring issues are more and more crucial in our everyday life. With the help of monitoring camera, by estimating age of the underage drinkers system can warn or stop him/her from entering bars or wine shops. In Japan, police found that a particular age group is more involved in money transfer fraud on ATMs, in which age estimation from surveillance monitoring can play an important role[2].

C. *Electronic Customer Relationship Management (ECRM)*

The ECRM [6] is a management strategy for effectively managing relationships with all customers and communicating with them individually. The most challenging part hereby is to obtain and analyze enough personal information from all customer groups to maintain long-term customer relationships. However, with the help of a computer-based automatic age estimation system, a camera snapping photos of customers could collect demographic data by capturing customers' face images and automatically labeling age groups[2].

D. *Age-based indexing and retrieval 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[5]. Indexing in the database of face images can be done on the basis of age. It is useful when retrieval of images is based on age such as to find out what percentage of teenagers prefers laptops over desktops.

E. Forensic Art

The forensic art is knowledge of shape of face, aging of human body. Age estimation by automated systems can be used as helping hand for forensic artists to create face sketch to find out possible suspects and for lost person identification[7].As a principal artistic technique in forensic art, age progression is used to modify and enhance photographs by computer or manually (with professional hand drawing skills) for the purpose of suspect/victim and lost person identification with law enforcement [2][8]. This technique has evolved when the photos of missing family members (especially children [2],or wanted fugitives are outdated, forensic artists can predict the natural aging of the subject faces and produce updated face images**.**

F. *Biometrics*

Age estimation is a type of biometrics that provides 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 biometrics system. In real face recognition or identification applications, it is often the case that the system needs to recognize or identify faces after a gap of several years [9][10] such as passport renewal and border security which reveals the importance of age synthesis.

III. AGE ESTIMATION SYSTEM

As shown in the diagram of Fig. 2, existing age estimation algorithm consists of three main stages, namely face preprocessing, feature extraction and estimator learning algorithm.

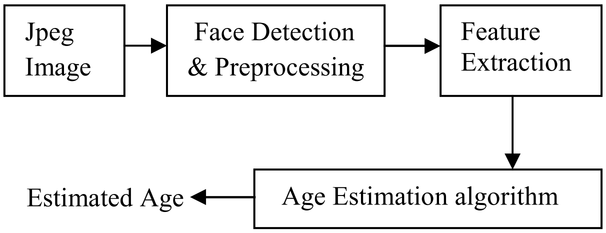

Fig. 2 Process of Age Estimation

A. Face Preprocessing

This includes detecting and cropping the face from the input image. Normalization of images is done before further processing, it can be contrast stretching, smoothening of image, noise removal, brightness normalization, geometric transformations etc.

B. Facial Feature Extraction

Features are defined as global, local or hybrid features. Changes from birth to adulthood are mainly in global features while the changes from adulthood to old age are in local features. The global and local features are combined to form hybrid features.

Researchers introduces following facial representation models[3]

- Anthropometric Model
- Active Appearance Model
- Aging Pattern Subspace
- Age Manifold.

Anthropometric model--

Facial Anthropometry is the science of measuring the size and proportions of the human face. Kwon and Lobo presented this work in[11]. The Anthropometric model based representations only consider facial geometry. This model computes six ratios of differences on frontal images. Craniofacial research theory uses a mathematical model (Eq. 1 & 2) for description of a person's head from birth to adulthood.

$$\Theta = \Theta' \qquad (1)$$

$$R' = R(1 + k(1 - \cos\Theta)) \qquad (2)$$

where Θ is the angle formed by the vertical axis, R is the radius of the circle, k is a parameter which increases with time, and (R', Θ') circuit growth over time[3].This model is useful for the classification of people in minors and adults, but it cannot distinguish between adults of different age.

Active Appearance Model--

Cootes et al.[12] Proposed this model. Based on PCA (Principal component analysis) shape and texture models are learned separately. Lanitis et al.[13] proposed the extended version of AAM

AAM uses the global features as it doesn't consider detail wrinkle and skin information. AAM is not only applicable to younger people, but for the people of all ages. This considers the geometry of human face and its texture also.

AAM vs. Anthropometric model--

AAM considers both the shape and texture, while the anthropometric model only involve facial geometry.
AAM based approaches can deal with any age, while the anthropometric model can be only used to distinguish minors from adults.

Aging pattern subspace--

This model was introduced by Geng et al.[14] and named AGES (AGing pattErn Subspace). This is personalized age estimation method. An aging pattern is a sequence of personal face images sorted in time order. Instead of dealing with each face image separately, this considers a sequence of images of an individual.

Age manifold--

A non-personalized approach was developed by the Guo et al. [15].Learning the common pattern of aging for more than one person at different ages is better than the learning the specific aging pattern for each person. More than one facial images of a person in one age or in an age range is used for age representation for each age. Therefore, this model is more flexible than AGES model, and it is much easier to collect a larger number of samples (facial images) and create a larger database. Guo et al.[15] performed age estimation using Locally Adjusted Robust Regression (LARR).

C. Age Estimation Algorithms

Estimator learning algorithms can be performed using either classification or Regression approach. In the classification approach different age groups such as 0-13, 14-22, 23-39 are formed and given subject is assigned to one of the group. On the other hand, regression method assigns exact numerical value making it more accurate. [17].

Classification--

Many methods such as k Nearest Neighborhood, multilayer perceptions, Artificial Neural Network (ANN), Support Vector Machines (SVM) and a quadratic function can be employed as a classifier for age prediction. Lanitis et al.[13] analyzed the performance of different classifiers for age estimation. It is observed that after performing experiments on a small database containing 400 images having age range from 0 to 35 years, quadratic function classifier can achieve 5.04 years of MAE, it is slightly lower than the nearest neighbor classifier, but higher than the ANN. Guo et al. applied SVM to age estimation[15] , [17] on a large YGA database with 8,000 images. The MAEs are 5.55 and 5.52 years for females and males, respectively.

Regression--

Some of the regression approaches are quadratic regression, gaussion proscess and support vector regression (SVR). Aging function has three forms: linear, quadratic, and cubic, respectively, with 50 raw model parameters. The model parameters are learned from training face images of different ages based on a genetic algorithm. Fu et al. [18], introduced a multiple linear regression function to fit the aging manifold, which achieves significant improvements over some existing techniques. Guo et al. [15],[17][19] applied The Support Vector Regression (SVR) method. The MAEs are 7.00 and 7.47 years on the YGA database for females and males, respectively, and 5.16 for the FG-NET aging database.

Hybrid Approach--

Hybrid approach is the combination of Classification and Regression. Guo et Al. [17] introduced a hybrid method Locally Adjusted Robust Regression(LARR) that combines classifier and a regressor to improve the accuracy of age estimation. This increases the performance, the MAEs can reach 5.25 and 5.30 years for female and male on the YGA database, and 5.07 years on the FGNET aging database, respectively.

D. Recent Work

Recently Jhony et al.[20] proposed a new framework for age estimation in which they used Binary Patterns (LBP), Gabor Wavelets (GW) and Local Phase Quantization (LPQ) to obtain highly discriminative feature representation to model shape, appearance, wrinkles and skin spots. Instead of classification or regression recent studies have proposed Learning-to-Rank approach in which ranking approach can be trained by adopting the ordering property of the labels. Kuang-Yu Chang et al.[21] have presented a cost-sensitive ordinal hyperplanes ranking algorithm for age estimation. Hu Han et al.[22] proposed a generic framework for automatic demographic (age,gender,race) estimation. For extracting the features they used boosting algorithm and then used hierarchical approach consisting of between group classification and within group classification. Baddrud et al.[23] introduced age estimation using Artificial Neural Network (ANN) and Gene Expression Programming (GEP). To get the good accuracy they used 29 neurons in the hidden layer of ANN. Yuan Dong et al.[24] proposed a deep learning based framework for age classification task. Using the deep convolution neural network they extracted high level complex age related visual features and predicted age.Rajan Jana et al.[25] proposed fuzzy c-means clustering algorithm for age estimation. Guo et al. [26] introduced the biologically inspired feature obtained from the feed forward model of the primate visual object recognition pathway.

IV. AGING DATABASES

Collecting large size aging databases is difficult task. We summarize some existing aging databases.

A. Face and Gesture Recognition Research Network (FG-NET) Database[27]

The FG-NET database is publicly available. It consists of 1,002 face images of 82 individuals with large variation of lighting, pose, and expression. Age range is from 0-69 years but over 50 % of the subjects in FG-NET database are between the ages 0 and 13.Each face image has 68 labeled landmark points.

B. MORPH Database[28]

Since FG-NET is a small database it is shown that its performance improvement tends to saturate. So effectiveness of an algorithm can also be compared using MORPH database that is larger than the FG-NET. Face Aging Group at the University of North Carolina at Wilmington collected this publicly available database. It is organized into two albums. Album 1 contains 1,724 face images of 515 subjects taken between 1962 and 1998.There are 294 images of females and 1,430 images of males. The age range is from 46 days to 29 years. Album 2 contains more than 20,000 face images obtained from more than 4,000 individuals.

C. YGA Database

The YGA database contains 8,000 high-resolution color images of 1,600 Asian subjects, 800 females and 800 males, with ages ranging from 0 (newborn) to 93 years. The photos contain large variations in illumination, facial expression, and makeup.

D. NI's Web-Collected Database

The Web collected database contains 219,892 faces from the flickr.com and the google.com image search engine. Age range is between 1-80 bases on query. This database is largest one for facial based age estimation.

V. EVALUATION PROTOCOLS FOR AGE ESTIMATION

To evaluate the performance of age estimation algorithms different measures are used. Commonly used two measures are Mean Absolute Error (MAE) and Cumulative Score (CS). The Mean absolute Error (MAE) is defined as the average absolute error between estimated and chronological age, that is,

$$MAE = \sum_{k=1}^{K} \left| \bar{I}_k - I_k \right| \Big/ N \qquad (3)$$

Where I_k is the ground truth age for the Kth test image and $\bar{I}_k$ is the estimated age. And N is the total number of test images.
The CS is defined as

$$CS(j) = N_{e<j} \Big/ \; N \times 100 \;\% \qquad (4)$$

Where $N_{e<j}$ is the number of test images on which age estimation makes an absolute error no higher than j years.

A. Comparison of Algorithms

Algorithms are compared based on Mean absolute Error (MAE) is defined as the average absolute error between estimated and chronological age. Algorithm having lower MAE is more better. FG-NET is most commonly used database.[3]

Table 1 Comparison of different algorithms

Algorithms	**Database**	**MAE**
K-Nearest Neighbour	FG-NET	8.24
Support Vector Machine	FG-NET	7.25
Aging Pattern Subspace	FG-NET	6.77
Manifold Learning ```	FG-NET	5.07
Active Appearance Model	FG-NET	4.37
Enhanced Bio Inspired Features	FG-NET	3.17
Support Vector Regression	FG-NET	5.16
Quadratic Function Classifier	YGA	5.04
Support Vector Machine	YGA	5.55
Support Vector Regression	YGA	7.47
LARR(Locally Adjusted Robust Regression)	FG-NET	5.07

VI. CHALLENGES

Though many researchers contributed and still working in this field, it is a challenging job as the process of facial aging is affected by intrinsic factors like change in shape and size of face, gene, and gender as well as by the extrinsic factors such as health, living style, eating habits, working environment, sociality, weather conditions and smoking. Other than this number of problems need to be addressed such as uncontrollable nature of the aging process, high variance of observations within the same age range, facial expressions, pose, blur, camouflage due to beards, moustache, glasses, and the difficulty to gather complete and sufficient training data.

VII. CONCLUSION AND FUTURE SCOPE

We have presented a complete survey of the techniques for age estimation via face images which has become very popular in recent decades because of their promising real-world applications in several emerging fields. Different facial age estimation approaches and algorithms can be used to get effective results. Comprehensive efforts from both academia and industry have been devoted recently for designing algorithms, for collecting face aging databases, and to improve system performance evaluation. So facial aging is challenging problem due to various problems discussed. However some of the problems have already been solved but still have room for improvement. Current techniques are still not robust enough for practical uses. So more robust and effective system need to be developed.

References

[1] S. Martinez-Conde, “Age progression,” *Nature*, vol. 527. p. 404, 2015.

[2] Y. Fu, G. Guo, and T. S. Huang, “Age synthesis and estimation via faces: A survey,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 11, pp. 1955–1976, 2010.

[3] P. Grd, “Introduction To Human Age Estimation Using Face Images,” vol. 21, pp. 24–30, 2013.

[4] X. Geng, Y. Fu, and K. S. Miles, “Automatic Facial Age Estimation,” *11th Pacific Rim Int. Conf. Artif. Intell.*, pp. 1–130, 2010.

[5] E. Kannan, R. R. Nair, P. Visu, and S. Koteeswaran, “Human Age Manifold Learning scheme and Curve Fitting for aging features,” *Int. J.*, vol. 1, pp. 490–494.

[6] “ECRM - Wikipedia.” .

[7] A. Kamra and S. Gupta, “Automatic Age Estimation Through Human Face : A Survey,” pp. 339–344, 2016.

[8] “Age Progression and Image Modification.” .

[9] K. Ricanek and E. Boone, “The effect of normal adult aging on standard PCA face recognition accuracy rates,” *Proc. Int. Jt. Conf. Neural Networks*, vol. 4, pp. 2018–2023, 2005.

[10] E. Patterson, K. Ricanek, M. Albert, and E. Boone, “Automatic representation of adult aging in facial images,” *IASTED’06 Proc. 6th Int. Conf. Vis. Imaging, Image Process.*, pp. 171–176, 2006.

[11] Y. kwo. and N. Lobo, “Age Classification from facial images,” *Comput. Vis. & Image Underst.*, vol. 74, no. 1, pp. 1–121, 1999.

[12] T. F. Cootes, G. J. Edwards, and C. J. Taylor, “Active Appearance Models,” *Proc. Eur. Conf. Comput. Vis.*, vol. 2, pp. 484–498, 1998.

[13] A. Lanitis, C. J. Taylor, and T. F. Cootes, “of Aging Effects on Face Images,” vol. 24, no. 4, pp. 442–455, 2002.

[14] U. Park, Y. Tong, and A. K. Jain, “Age-invariant face recognition,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 32, no. 5, pp. 947–954, 2010.

[15] G. Guo, Y. Fu, C. R. Dyer, and T. S. Huang, “Image-based human age estimation by manifold learning and locally adjusted robust regression,” *IEEE Trans. Image Process.*, vol. 17, no. 7, pp. 1178–1188, 2008.

[16] Z. Li, U. Park, and A. K. Jain, “A discriminative model for age invariant face recognition,” *IEEE Trans. Inf. Forensics Secur.*, vol. 6, no. 3 PART 2, pp. 1028–1037, 2011.

[17] G. Guo, Y. Fu, T. S. Huang, and C. R. Dyer, “Locally adjusted robust regression for human age estimation,” *2008 IEEE Work. Appl. Comput. Vision, WACV*, 2008.

[18] Y. F. Y. Fu, Y. X. Y. Xu, and T. S. Huang, “Estimating Human Age by Manifold Analysis of Face Pictures and Regression on Aging Features,” *Multimed. Expo, 2007 IEEE Int. Conf.*, pp. 1383–1386, 2007.

[19] S. Yan, H. Wang, X. Tang, and T. S. Huang, “Learning auto-structured regressor from uncertain nonnegative labels,” *Proc. IEEE Int. Conf. Comput. Vis.*, 2007.

[20] J. K. Pontes, A. S. Britto, C. Fookes, and A. L. Koerich, “A flexible hierarchical approach for facial age estimation based on multiple features,” *Pattern Recognit.*, vol. 54, pp. 1–18, 2016.

[21] Kuang-Yu Chang and Chu-Song Chen, “A Learning Framework for Age Rank Estimation Based on Face Images With Scattering Transform,” *IEEE Trans. Image Process.*, vol. 24, no. 3, pp. 785–798, 2015.

[22] H. Han, C. Otto, X. Liu, and A. K. Jain, “Demographic estimation from face images: Human vs. machine performance,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 37, no. 6, pp. 1148–1161, 2015.

[23] B. Z. Laskar, Ashutosh, and S. Majumder, “Artificial Neural Networks and Gene Expression Programing based age estimation using facial features,” *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 27, no. 4, pp. 458–467, 2015.

[24] Y. Dong, Y. Liu, and S. Lian, “Automatic age estimation based on deep learning algorithm,” *Neurocomputing*, vol. 187, pp. 4–10, 2016.

[25] R. Jana, D. Datta, and R. Saha, “Age estimation from face image using wrinkle features,” *Procedia Comput. Sci.*, vol. 46, no. Icict 2014, pp. 1754–1761, 2015.

[26] G. Guo, G. Mu, Y. Fu, and T. S. Huang, “Human age estimation using bio-inspired features,” *2009 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit. Work. CVPR Work. 2009*, pp. 112–119, 2009.

[27] “The FG-NET Aging Database.” .

[28] “MORPH Face Database.” [Online]. Available: http://faceaginggroup.