A Survey on Facial Age Estimation Based on Multiple CNN

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Abstract— Age estimation is predicting someone's age by analyzing his/her biometric traits like fingerprints, bone density, dental structure and face. Out of these characters, face is most convenient to capture and analyze. Also it is easy to automate age estimation systems that use face as input. Because of its real life applications, researchers have shown great interest in automatic facial age estimation. This paper, discussed about the problems that are being faced. This paper highlights latest methodologies and feature extraction methods used by researchers to estimate age.

Key words: Face, Facial Age Estimation, Face Detection, Feature Extraction, Classifiers

I. Introduction

Human face serves as a pool of useful information about the person such as identity, age, ethnic group, gender, posture, and expression. Facial age estimation has become a prominent topic in recent years due to its many possible applications, such as surveillance, electronic vending machines, security control, forensic art, entertainment, and cosmetology. However, regardless of the ongoing growth in the field of age estimation, it is still a challenging job as the process of facial aging is affected not only by intrinsic factors like change in shape and size of face, but also by extrinsic factors, such as manner of living, eating habits and environment. Furthermore, surgical marks, the presence of facial scars, facial cosmetics and even dense facial hair can create hindrance in accurate working of facial age estimation systems. So, a survey was done among different proposals and this survey paper includes survey among different methods for facial age estimation.

II. Motivation

There are many popular real world applications that are directly or indirectly related to facial age estimation. Age estimation through automated systems is useful when we need to label person with age instead of his/her identity.

A. *Forensic Art*

The forensic art is knowledge of shape of face, aging of human body, psychology, perception. As a basic practice in forensics, changes in face due to age progression are projected in photographs by automated systems or by professional artists to include age effects. Automated systems age estimation can be used as serving hand for forensic artists to create face sketch.

B. *Age Based Retrieval for Face Image*

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.

C. *Security Control*

Face is most easily biometric trait that can be used in security systems to identify a user. Face recognition is being widely used to secure the confidential systems/rooms/hard drives from unauthorized users. Time is the only barrier which hinders the quality of security provided by face recognition systems because the face of user changes as it ages. This can be eliminated by combining facial age estimation with face recognition that is age invariant face recognition systems.

D. *Surveillance*

Now a day's surveillance monitoring is one of the most difficult jobs as explosive information is now easily accessible. Underage people and minors can be warned from entering wine shops and bars or from purchasing tobacco by using a monitoring camera and the age estimation system. Children can also be refused from accessing adult Websites or watch restricted movies by using the same.

III. Literature Survey

Zhenzhen Hu et al. [1] propose a facial age estimation with age difference. Age estimation based on the human face remains a significant problem in computer vision and pattern recognition. In order to estimate an accurate age or age group of a facial image, most of the existing algorithms require a huge face data set attached with age labels. This uses a constraint on the utilization of the immensely unlabeled or weakly labeled training data. These images may provide no age label, but it is easily derive the age difference for an image pair of the same person. To improve the accuracy of age estimation, propose a novel learning scheme for weakly labeled data- via the deep Convolutional Neural Networks (CNNs). For each image pair, Kullback-Leibler divergence is employed to embed the age difference information. The entropy loss and the cross entropy loss are adaptively applied on each image to make the distribution exhibit a single peak value. Here also contribute a dataset including more than one hundred thousand face images attached with their taken dates. Each image is both labeled with the timestamp and people identity.

Xiaolong Wang et al.[2] propose a age estimation via unsupervised neural networks. Which investigate an unsupervised neural network framework for the problem of facial image age estimation. Unlike previous approaches in age estimation where a predefined feature extraction framework is used, the features used in this system are directly learned from the data. A single layer convolutional neural network and recursive convolutional neural networks are used to extract features from an image. Manifold learning scheme is incorporated in the framework, which maps the features into the discriminative subspace. Furthermore, several popular regression and classification methods are evaluated using this scheme. This is the first system where an unsupervised neural network has been introduced to the age estimation problem. Here, evaluate the proposed scheme on two widely used datasets.

Furkan Gurpınar et al.[3] propose a two-level system for apparent age estimation from facial images. The system first classifies samples into overlapping age groups. Within each group, the apparent age is estimated with local regressors, whose outputs are then fused for the final estimate. For this use a deformable parts model based face detector, and features from a pretrained deep convolutional network. Kernel extreme learning machines are used for classification due to the learning speed and accuracy of the algorithm. A simple and robust learning algorithm is proposed by ELM for single-hidden layer feed forward networks. The input layer's bias and weights are initialized randomly to obtain the output of the second (hidden) layer. The bias and weights of the second layer are calculated by a simple generalized inverse operation of the hidden layer output matrix.

Koruga et al.[4] proposed modeling age progression in young faces. Which define anthropometric model such that this method employs the cranio-facial development theory and skin texture analysis to develop the aging model. This model is very useful in modeling faces at young ages but not apt for adults. Changes that occur in shape and texture patterns due to age progression are analyzed to categories age into age groups. It is mostly used for coarse estimation rather than fine refinement. The anthropometric model describes the growth of a person's head from infancy to adulthood for age representation. Where, face anthropometry is the science of measuring sizes and proportions on human faces. This method is limited because human head shape does not change too much in adult period.

K. Luu et al.[5] proposed an active appearance model. It is a computer vision algorithm that matches a statistical model based on object shape and appearance to a new image. Training is done by using a set of images and their facial landmarks that appear in all of the images. To study the variation in age, lanitis proposed aging function age = f(b) where age is actual age of person, b is parameters in vector representation obtained by extending AAMs. The aging function establishes relationship between the age of individuals and description of the face images. Quadratic aging function was used to understand relationship between actual ages and function. AAMs give analysis for all the ages where as anthropometric model works for child to young age as in [6]. AAM model based approaches consider shape and texture and not only facial geometry.

X. Geng et al.[6] proposed an aging pattern subspace (AGES)which uses sequence of an individual faces at different stages of life together to represent aging process. The sequence of individual ages at each stage of life in temporal order is called aging pattern. If all the images of person in temporal order is available then it is called complete aging pattern otherwise incomplete aging pattern. The AGES can synthesize the missing ages by applying iterative learning algorithm such as expectation maximization algorithm. Firstly images are encoded by Lanitis active appearance model (AAMs) method and along with active appearance model encoding, it also consider aging pattern of individuals. AGES method have issue that it requires sequence of images of individual of person as in input image or similar of input face. This assumption or criteria cannot be satisfied always in terms of datasets. Intensities of single pixels usually lack local texture information representation completely and AAM uses intensities of single pixels. Due to use of intensities of single pixels the wrinkle analysis is not achieved properly for older aged faces in AGES method as it is not easy to find images of older faces and to form aging pattern.

Y. Fu et al.[7] proposed an age manifold method. Age manifold learns aging pattern from many individuals rather than single people's images at different age. The missing age image analysis is obtained from many individuals of same age using PCA approach. Age manifold adopt many faces for representing missing age. Due to such mechanism it is not always necessary to have all the images of individual that makes it flexible than aging pattern subspace (AGES) approach. In manifold embedding, it learns low dimensional aging pattern of individual at different ages from. In worst case, only one

Image of individual may also present representing single age. This helps when large database of images is available. The goal of manifold is to capture intrinsic data distribution & geometric structure by using low dimensional representation of embedded subspace. A large database is required to learn missing ages is the limitation of age manifold method.

Sai Phyo Kyaw et al.[8] propose an web image mining for facial age estimation. Face image based age estimation is an approach to classify face images into one of several pre-defined age-groups. It is demanding because the aging variation is specific to a given individual and is determined by not only the person's gene, but also by many external factors, such as exposure, weather conditions (e.g. ambient humidity), health, gender, living style and living location. Age categorization is a multiclass problem. Lack of a good public aging dataset makes it difficult to estimate age from face image. Due to large multiclass nature of human ages, it is difficult to collect large aging database. Here proposed a novel approach to collect high quality aging face images. Application Programming Interface (API) services provided by Microsoft Search Engine Bing are adopted for this purpose. Automatic collection of age-specified query images was implemented in C# programming interface with Microsoft BING API services. The aging images are collect as huge volume from internet hosts, which contain a large number of images with age labeling. It serves as an alternative cheap platform to gather face images for age classification.

Asuman GÜNAY et al.[9] proposed an automatic age classification with LBP. Estimating the age exactly and then producing the younger and older images of the person is important in security systems design. Here local binary patterns are used to classify the age from facial images. The local binary patterns (LBP) are fundamental properties of local image texture and the occurrence histogram of these patterns is an effective texture feature for face description. In the study classify the FERET images according to their ages with 10 years intervals. The faces are divided into small regions from which the LBP histograms are extracted and concatenated into a feature vector to be used as an efficient face descriptor. Spatial LBP histograms are produced and used to classify the image into one of the age classes for every new face presentation. In the classification phase, minimum distance, nearest neighbor and k-nearest neighbor classifiers are used. The experimental results have shown that system performance is 80% for age estimation.

F. Gao et al. [10] propose an Face age classification on consumer images with gabor feature and fuzzy-Method. Face age estimation task is not only challenging for computer, but even hard for human in some cases, however, coarse age classification such as classifying human face as baby, child, adult or elder people is much easier for human. So, here try to dig out the potential age classification power of computer on faces from consumer images which are taken under various conditions. A fuzzy version LDA is introduced through defining age membership functions for to solve the intrinsic age ambiguity problem. Systematic comparative experiment results show that the proposed method with Gabor feature and fuzzy LDA can achieve better age classification precision in consumer images.

IV. Facial Aging Database

Over the years, numbers of datasets of facial images have been used to analyze and study the issues related to face recognition and facial expression analysis. In the face of numerous sources there is difficulty in compiling face datasets to be used for facial age estimation as not all databases comprise of face images at different ages. Some of the popular databases that specifically address facial aging are:

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

This database is a collection of 1002 images gathered from 82 subjects (approximately 8-10 images of each subject). Age range of database is 0-69. Images are captured in an uncontrolled manner, having large variation of illumination, posture, and facial expressions. For every file containing facial land marking points is also there along with actual age of subjects.

B. MORPH Database

The database has been separated into two sub-databases, named as: MORPH Album 1 and MORPH Album 2. Morph Album 1 contains 1,724 face images of around 515 subjects. Age range of this database is distributed over 15–68 years. Morph Album 2 was gathered from about 4000 individuals. Total number of images in this sub-database is 15204 images.

C. YGA Database

It contains 8000 color images of 1600 subjects, out of which 800 are females and 800 are males. Each subject is having on an average 5 frontal face images. Age range of this database is 0 to 93.

D. Waseda Human-Computer Interaction Technology-DataBase (WIT-DB)

This database comprises of images collected from more than 5000 different subjects of Japanese origin. It includes around 2500 females and 3000 male subjects. It has 1-14 images per subject.

Sr.No.	**Method**	**Parameters**		**Advantage**	**Limitation**
		MAE in years	**Accuracy**		
1	Anthropometric models[4]		Very less accuracy	Basic model for age estimation	Work for child and Adult classification
2	Active shape Model [5], Active Appearance Model [5]	MAE 4.37 for FGNET.		AAM is better than ASM	AAM fails between youth and Adults.
3	Aging pattern Subspace [6], Age Manifold [7]	MAE 6.77 for FGNET and 8.83 for MORPH Dataset		Age pattern analysis is very well carried out.	Analysis of neighborhood fails. Required many images of single person and very large dataset
4	Local Binary Pattern [9]		80% KNN	Fast feature extraction	Decreases accuracy when global feature analysis is considered.
5	Gabor Filters [10]		Accuracy is 91% with LDA approach	More effective than LBP. Invariant to illumination and orientations.	Higher number of feature vectors
6	Bio-Inspired Feature [8]	MAE is 4.77 for FGNET		Most effective from all based on MAE. Tested for cross dataset and on few web images.	As it goes deeper in layer, its complexity increases.
7	Convolutional Neural Network [1] [2] [3]		96.43% with SVM Audience Dataset.	Compared with gabor feature the accuracy is higher. Distortion Invariant	Requires large amount of training dataset

Table 1

E. Vietnamese Longitudinal Face (VLF) Database

VLF database has 227 Vietnamese colored images of 28 subjects, comprising of 12 males and 16 females. Age range of subjects is between 1 to 80 years of age. Each subject has around 8 frontal pose images provided along with ground truth age and annotated with 68 landmarks. This database is collected for analyzing growth and development stage and facial heredity of familial members.

F. Iranian Face Database

IFDB contains over 3600 color images that were captured from 621 Caucasian faces. Subjects have age range from 1 to

85years. Database includes 4 different poses, 2 different expressions and one image with spectacles of every subject. Information regarding plastic surgeries, age, skin type, occupation, fingure prints is also collected from subjects.

V. CONCLUSION

In this paper recent works in the field of age estimation was discussed. Many researchers had contributed and are still working in this field. Though there is number of problems in existing systems that need to be addressed such as occlusion created by spectacles, cap or facial hairs, uneven illumination. However some of the problems like non frontal pose, collection of images along with their age on large scale have already been solved but still have room for improvement. From the analysis of feature extraction phase, different methodology prevails like 1) Local feature extraction: LBP and Gabor filters extract features locally. 2) Global feature extraction: AAM, AGES, Age manifold, BIF and CNN extract features globally. 3) Extracting both local and global features. It is concluded, local features can bring minute texture details that are necessary for wrinkle analysis and estimation of older ages. In all-purpose, different facial age estimation approaches and algorithms can be used to get effective results in different real life scenarios.

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