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A Survey on Recent Advances in Facial Age Classification

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Abstract

Facial age classification, a new dimension that has recently has been added to the problem of face recognition which created interesting theoretical and practical challenges to the research community nowadays. The problem which originally created interest in the psychophysics and human perception community and has recently found enhanced interest in the computer vision community. How do humans perceive age signs in face? And what constitutes an age-invariant signature that can be derived from faces? How does facial aging impact recognition performance? All these questions created an interest with us and in this paper we present a survey on state of art techniques of facial aging assessment problem using digital images. A comprehensive analysis on various attributes to aging estimation and comparative analysis of recent age estimation techniques, models, evaluation difficulties and performance assessment are reported along with promising future work directions.

Keywords: Facial age estimation, Age Classification techniques, Facial image Database, Face detection, Face Recognition.

Introduction

Digital images are the collection of millions of information. Facial image is a repository of such wider facial information. The growth of digital cameras and camera based handheld devices rapidly increasing the size of face databases broader. Photobook, picasa, flicker, phanfare, smugmug, zenfolio, etc are famous photo management applications. The growth of these facial image databases ultimately needs an effective facial recognition and detection mechanisms. The facial recognition systems are often fails when a facial database gets older or a person with age separated images. The face recognition system could not understand the aging progression of a person. Analyzing person's age from an image of the person's face is an easiest task for a normal human being, where as this process is very difficult to computer system [5]. To address this problem, there have been number of approaches and varieties of models are available. Human aging is a continuous accumulation process over a period of time. Aging is a slow and irreversible process or may be slightly reversible process. The chronological aging is fully time dependent biological process to change in structure and functional attributes of human body. The internal changes are not visible and hard to observe. The extrinsic aging is another aging process by several external factors. Pollution, nutrition imbalance, smoking, sleeping deprivation and hard sun light are few of the factors of extrinsic aging process. In both the aging process, it is inevitable to many changes in human body. Among the various physical components of human body face and skin textures represents valuable aging information. The face age estimation process offers significant benefits to human community. Forensic art, electronic customer relationship management system, security control and monitoring systems, entertainment, and cosmetology are few of applications that use age estimation process. The wider application requirements of face detection and recognition are due to the wider security demands, increased photo gallery usage and face based authentication services. The demands of face detection and recognition have been addressed by various researchers but, there are limited techniques that provide a robust solution to various situations. Face recognition is a trivial task for the human brain and it has been proved to be extremely difficult to imitate artificially, as commonalities exist between faces. These commonalities can vary considerably in terms of age, skin color, orientation, facial expression and presence of facial furniture such as glasses or facial hair. Face detection is a fundamental step in face recognition systems, with the purpose of localizing and extracting the face region from the background. Human visual systems are characterized by the fact that the face is perceived as a whole, not as a collection of the facial features. How accurately the system imitate is the success of age estimation system. The rest of the paper is organized as follows, the section 2 brief the motivation behind our work. Section 3 discusses various facial age estimation techniques and in section 4 we discuss different facial databases that are currently available and used for research process and sections 5 conclude our observation with open issues found in this domain.

Motivation Behind

Aging is a continuous and irreversible activity to every living organism. To recognize such an aging changes, our intelligence systems are working together and supporting to knowledge building. Bring these intelligent mechanisms to computer systems, there has been number of techniques proposed and widely in use. Hjelmas and Boon [26] conducted a survey on face detection techniques, and identified two broad categories that separate the various approaches, namely Feature-based approaches and Image-based approaches. Fig.1 illustrates the different approaches for face detection. Facial features were used in many researches such as recognition, classifying gender, expressions, age classification and so on. Recognition of the most facial variations, such as identity, expression and gender has been extensively studied. Automatic age estimation (AAE) has rarely been explored. In contrast to other face variations, aging variations presents several unique characteristics which make age estimation a challenging task. Age estimation is determination of a person's age based on biometric features. The determination of the age of a person from a digital photography is an intriguing problem which involves understanding of the human aging process.

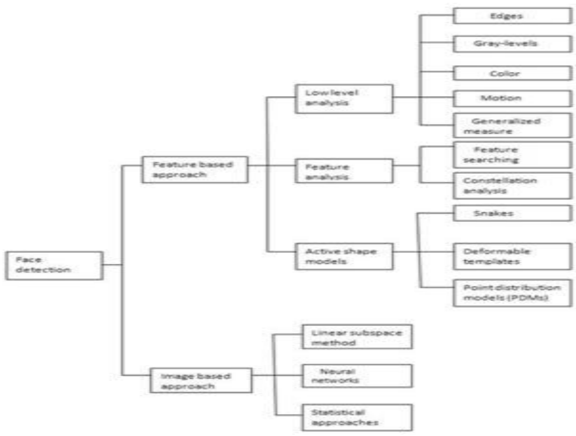

Figure 1: List of face detection techniques

Although an intriguing problem, we found numerous techniques and approaches in our computer vision community. This survey tries to find the insights of each technique and possibly helps to understand these techniques much easier.

Age Classification Techniques

Facial features were used in many researches such as recognition, classifying gender, face expressions recognition and so on. But few of them have been done on age classification especially on age estimation. The materials assessed were categorized into five main groups namely,

1. Anthropometric model (AM).
2. Aging pattern Subspace (AGES) model.
3. Regression model (RM).
4. Appearance based approach (APM).
5. Active Appearance model (AAM).

Anthropometric model

The anthropometric model [1] has been proven to be very successful for human age estimation. Human face texture (part of anthropometric model) is chosen as the prevailing feature of human age estimation process. The texture information was extracted using Gabor Wavelets. A combination of Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) was applied on the Gabor faces for dimension reduction and to enhance the class separability. By applying PCA to the Gabor face images, low dimensionality images were obtained and processed using LDA. The vectors obtained from the LDA are representative of each image. These vectors were divided into train vectors and test vectors. The train vectors were used to train the system. Finally Euclidean distance between the test vectors and the train vectors classified the train vectors into one of three age groups namely Group1 (0 to 3 years), Group2 (5 to 10 years) and Group3 (20 to 80 years). The major drawback of this approach is it may not be useful to differentiate adult and senior adults or adults of different ages.

Gabor Feature and Fuzzy LDA Method

In this method the Gabor feature is extracted for face representation and used in LDA classifiers. In order to solve the intrinsic age ambiguity problem, a fuzzy version LDA is introduced through defining age membership functions. In this partitioning of age is classified into four categories, which are baby (0 to 1 approximately), child (2 to 16 approximately), adult (17 to 50 approximately), and old (after 50 approximately). Gabor features [2] as face representation and linear discriminant analysis (LDA) are used to construct the final age classifier.

Gabor Features:

Gabor Features are popular in face representation; their effectiveness has been proved by many researches in fields like face recognition. In facial age classification, Gabor features of 3 scales and 4 orientations that amount to 12 convolved face images of which only magnitude images are used as raw features are extracted. PCA is used for dimension reduction.

Fuzzy LDA:

Linear discriminant analysis (LDA) as a classical dimension reduction method aims to find out optimal project directions to maximize the ratio of between-class scatter and minimize the within-class scatter. After finding the projected directions, data can be mapped to low-dimensional subspace, and the nearest class center criteria is used for classification. In LDA method, each training sample is assigned to one class label exactly, this is easy in many other classification problems, because these classes have been clearly defined. But in age classification, mapping ages to age groups is somewhat intrinsically ambiguous. There are three ways to achieve this goal:

1. Drop some vague ages.
2. Assign every age to only one age group.
3. Assign every age to all age groups with the help of fuzzy age membership functions.

In fact, the above three can also be expressed through age membership functions based on fuzzy mathematics. With the introduction of fuzzy age membership functions, the LDA method is modified to a fuzzy version to suit the age classification problem.

Facial Features and Back Propagation

Wen-Bing Horng [3] has proposed an age group classification system for gray-scale facial images. Four age groups, including babies, young adults, middle-aged adults, and old adults are used in the classification system. The process of the system is divided into three phases: location, feature extraction and age classification. In the location phase, the symmetry of human face helps to find the vertical central lines of the face. Since eyes, noses and mouths have significant brightness changes the Sobel edge operator and region labeling are applied to locate them. Both geometric and wrinkle features are employed in the system for classification. In the feature extraction phase, two geometric features are evaluated as the ratios of the distances between eyes, nose and mouth. Three different wrinkle features used are

- Wrinkle density,
- Wrinkle depth,
- Average skin variance defined to quantify the degrees of facial wrinkles.

In the age classification phase, two back propagation neural networks [4] are constructed. The first one employs the geometric features to distinguish whether a facial image is a baby. If not, then second network uses the wrinkle features to classify the image into one of the three adult groups. Notice that the dynamic range of each facial image is different. Thus, the preprocessing of histogram stretch operations is performed on all experimental images so that the ranges of gray-level of all images are mapped to the range [0, 255].

Aging pattern Subspace (AGES) model

Xin Geng et al. [6] developed an age estimation method named AGES (Aging pattErn Subspace) based on the following assumptions,

1. The aging progress is uncontrollable.
2. Every person will have different age.
3. The aging progress must obey the order of time.

Therefore the aging patterns are introduced as a sequence of personal facial images sorted in chronological order. The images are represented by their feature vector, extracted by the Appearance Model described in [7]. Instead of using isolated pictures for training, a subspace of the aging patterns is learned using Principal Component Analysis (PCA). The big problem was the lack of complete aging patterns which leads to highly incomplete training data. To deal with this, the first step is an iterative learning algorithm that was developed estimate a part of the missing personal aging pattern in each iteration process using the global aging pattern model. When estimating the age, the feature vector of the image is calculated and is used to find a suitable aging pattern in the subspace. In the second step the proper position in the determined aging pattern is indicated by the minimal reconstruction error that to deal with expression variations, pose and illumination. Two-layer age estimation is constructed using AGES to classify the test samples into the three most consistent age ranges. Three separately trained subspaces are used to assign the exact age.

Linear Wavelet Transforms

An innovative technique that classifies adult images with age spans for every ten years based on the topological texture features in the facial skin. It assumes that bone structural changes do not occur after the person is fully grown that is the geometric relationships of primary features do not vary. That is the reason why secondary features are identified and exploited. The secondary features that are exploited in this approach are Topological Texture Features (TTF) [7] on two-level linear wavelet transform of the facial skin. A face can be represented in this new space by a few weights. Recognition is considered successful when an image's weights fall within some neighborhood of a set of weights already stored in a database. This method is sensitive to scale, viewing angle, lighting changes, and background noise. The facial skin of a person tends to more changes with growing age. These rapid topological changes in the skin are exploited by TTF's. For classification of adult age groups into seven categories the grey level images of each group are converted into binary by taking care of noise factor. Then frequency of occurrence of each TTF on 2-level LL-Sub band image is computed. From this Global Topological Texture Features (GTTF) on each part is evaluated. The GTTF is the sum of all TTF's count on each part of the facial image. Average value of all GTTF count of each part of the facial image on each group is calculated, and is placed in Topological Skin Aging Database (TSAD).

Regression model

Sethuram et al. [9] improved the analysis-synthesis face-model approach, which is based on Active Appearance Models (AAM). He used Support Vector Regression (SVR) to learn age-based properties of the AAM parameters and gradient-regression-based AAMs, to represent the texture information. After this a Monte-Carlo simulation is run, which generates random faces, which are then classified based on the age estimated by the SVR, to get the feature information learned by the support vectors. Finally bins are created and averaged for each age, to get a table of AAM parameters that can be used to morph a face to a desired age. The performance of building one general model and having a model for every ethnicity, gender and age group combination are compared. Two ethnic groups of American and African and the two age groups 18-45 and 46-65 years are considered for evaluation. Khoa Luu et al. [21] used Active Appearance Model (AAM) to extract a combined feature vector of the facial images. The classifier is divided into two steps. First, a binary classifier f is build by SVMs to distinguish between youths (0-20) and adults (21-69). In the second step, a growth and development function *f1* and an adult aging function *f2* are separately trained with Support Vector Regression (SVR) [21], on youth and adult datasets, respectively. When classifying, the test images are initially assigned to one of the two age groups and then handed to the corresponding age function, to estimate facial ageing. Based on this work Khoa Luu et al. modified the classifier construction by adding a supervised spectral regression after the extraction of the combined AAM feature vector [21]. It should improve the correlation information among the feature vectors of the same class and decrease it for different classes. Also it should help to reduce the dimension of the feature vector. Carmen Martinez and Olac Fuentes [10] proposed a method to improve accuracy when only a small set of labeled examples are available using unlabelled data. Eigenface technique is applied to reduce the dimensionality of the image space and ensemble methods to obtain the classification of unlabelled data. Ensembled unlabeled data chooses the 3 or 5 examples for each class that are most likely belong to that class. These samples are appended to the training set in order to improve the accuracy and the process is repeated until no more examples to classify. The experiments were performed using k-nearest-neighbor, Artificial Neural Network (ANN) and locally weighted linear regression learning.

Manifold Learning and Locally Adjusted Robust Regression

The basic idea is to learn a low-dimensional embedding of the aging manifold using an appropriate subspace learning method. The new method called locally adjusted robust repressors (LARR) is developed for robust learning and prediction of the aging patterns [11]. The age estimation framework mainly consists of five modules: face detection, face normalization, manifold learning, robust regression, and local adjustment. For training, face image patches are automatically detected and cropped from images by face detection. Some typical dimensionality reduction and manifold embedding methods are

1. Principal Component Analysis (PCA): The PCA method finds the embedding that maximizes the projected variance; where is the scatter matrix, and is the mean vector of the PCA method is mentioned here because it is very popular for many tasks such as face recognition.
2. Locally Linear Embedding (LLE): The LLE algorithm seeks the nonlinear embedding in a neighborhood preserving manner by exploiting the local symmetries of linear object class reconstructions, and seeking the optimal weights for local reconstruction.
3. Orthogonal Locality Preserving Projections (OLPP): The OLPP method produces orthogonal basis functions based on the LPP to obtain more discriminating power for embedding. The LPP searches the embedding that preserves essential manifold structure by measuring the local neighborhood distance information. It defines the affinity weight as when and is nearest neighbors of each other, otherwise, and is a symmetric matrix. It also defines a diagonal matrix, and a Laplacian matrix, and then the optimal projection is associated with the smallest eigenvalue.

Quadratic Regression

The extracted features for each face image, a regression function are often used to characterize the relationship between the extracted features and the age labels. The typical choice of the regression function is the quadratic model (QM). There are some disadvantages for the QM method:

1. The aging is a complex nonlinear regression problem, especially for a large span of years, e.g., 0–90. The simple quadratic function may not model properly the complex aging process.
2. The least square estimation is sensitive to outliers that come from incorrect labels in collecting a large image database

3. The least square estimate criterion only minimizes the empirical risk which may not generalize well for unseen examples, especially with a small number of training examples. This is typical in age estimation because of the difficulty in collecting age images and the diversity of age patterns due to different living conditions, cosmetics, gender differences, and facial shapes.
4. A robust model for modeling the aging patterns is needed. For the purpose of robust regression of the aging process, the support vector regression (SVR) method is adopted. The SVR might attack the three limitations of the traditional quadratic regression model to facilitate the age estimation task.

Support Vector Regression

The basic idea of SVR is to find a function f(Y) that has most € deviation from the actually obtained target Zi for the training data Yi, and, at the same time, is as flat as possible. This property determines the SVR to be less sensitive to outliers than the quadratic loss function. Given the same input, the insensitive loss function is more robust than the quadratic function in dealing with outliers. A nonlinear regression function may be required in practice to adequately model the data. It can be obtained by using kernels, in the same manner as a nonlinear support vector machine (SVM) for classification. A nonlinear mapping can be used to map the data into a high-dimensional feature space where a linear regression is performed.

Embedded Hidden Markov Model

Ye Sun et al., [12] presented Embedded Hidden Markov Model (EHMM) to recognize face and age. The nonlinear relationship between the key feature points in the face and different ages of the same face are used to train EHMM to estimate ageing face. Allison C Lamont et.al., [22] presented a study on recognition accuracy based on ageing effects.

Radon transform and entropy based scaling SVM

This method is used to extract perceptual features by applying difference of Gaussians (DoG) filtering to a face image. These features are then processed using a radon transform in order to diminish the effects of in-plane facial rotation, which often occurs in realistic face images. Afterwards, to achieve correct age classification using appropriate attributes, an improved adaptive scaling approach for feature selection in a support vector machine (SVM) classifier has been proposed. The proposed approach is efficient, unsupervised, and does not require face segmentation. Age classification algorithm begins by DoG filtering [13]. This is followed by applying the Radon transform to the DoG filtered images, leading to so-called “Radonmaps" containing Radon coefficients of the face image. The Radon coefficients are then dynamically and adaptively optimized for age classification within the framework of an automatic scaling SVM.

Learning Vector Quantization (LVQ)

Vector Quantization is an extended application of Correlation Templates, the theory described here is largely based on the LVQ PAK compendium [23]. One approach is to use different forms of templates. These templates incorporate some type of knowledge about the problem domain of face recognition; some of this knowledge is encoded manually into the template approach (e.g. creating templates for eyes, nose or mouth).

Correlations Templates:
Correlation Templates is a filter technique, the difference between the candidate image and a face template is calculated by comparing the pixel values in the Correlation Template [25] to the pixels in the candidate image.

Sambu et al., [24] also showed that with this limitation on the update rule LVQ obtains similar margin maximization properties as the Support Vector Machine (SVM) algorithm. SVM is yet another Machine Learning technique useful for finding class borders in a sample space. When compared with the LVQ approach, SVM selects the samples that lie on the class border and use them to classify any unknown sample. LVQ2.1 updates the Feature Vectors only according to samples that lay on the class border instead to achieve similar results.

Min-Max Modular Support Vector Machine
Ryotatsu Iga et al., [17] developed an algorithm to estimate Gender and Age (using SVM) based on features like geometric arrangement and luminosity of facial images. The graph matching method with Gabor Wavelet Transform (GWT) method is used to detect the position of the face. GWT features, texture spots, wrinkles, and flabs are used for age estimation. Hui-Cheng Lain and Bao-Liang Lu [18] proposed Min-Max Modular Support Vector Machine (M3- SVM) to estimate age. Facial point detection (GWT) and retina sampling method is used to extract features from face images. The task decomposition method is used in M3-SVM to classify gender information inside age samples.

Appearance-based approach
The appearance-based approach will be used as in most face recognition systems. However, features should be robust against various lighting conditions, and feature extraction should be processed in real-time. They would like to focus on the dimensionality reduction, which can reduce computational cost and lighting variations, and can improve the separability in age-groups. Kalamani et al. [19] applied Fuzzy Lattice Neural (FLN) model to age classification system. Three winkle features; winkle density, wrinkle depth and average skin variance. In this dissertation introduce new age-group classification algorithms called 2DLDA and 2DHDLA in order to improve the classification rates, where a large data set was created and age-groups are subdivided into smaller age-groups such as 5 or 10-year range age-groups. Appearance-based approaches are adopted as a feature extraction method. This is commonly used for real-world applications such as face recognition and gender classification systems for the reason of practicality. The appearance-based approaches find the decision boundary from training images without extracting any geometric features, whereas the geometry-based approaches need high-resolution images in

order to extract the precise positions of facial features such as eyebrows, nose, wrinkles, etc.

Facial Image Databases

Facial image dataset are the vital component to any face detection or face recognition system. Collecting and organizing face database is a resource-intensive work. The availability of public face database is an important advantage of this field. In table 1 we show few reputed facial databases with its technical specification and features.

Table 1: Face Database and Specification

Database for Face recognition					
Sl.No	**Name of the Database**	**Size in Images**	**Subjects**	**Features**	**Availability**
1	AR Database	4000	120	Facial Expression and Illuminations	http://www2.ece.ohio-state.edu/~aleix/ARdatabase.html
2	BANCA database		208	Gender group	http://www.ee.surrey.ac.uk/CVSSP/banca/
3	CAS-PEAL Database	1 Million	1040	Pose, Expression, Accessories, and Lighting	http://www.jdl.ac.cn/peal/
4	CMU-PIE Database	7.5 Millions		Pose, Illumination and Expression	-
5	Equinox Infrared Face Database		91	Illumination, Expression	http://www.ri.cmu.edu/projects/project_418.html
6	FERET Database	14051	1199	Expression, Illumination, Pose, Time	http://www.itl.nist.gov/iad/humanid/feret/feret_master.html
7	KOREAN Face Database	52,000	1000	Pose, Illumination, Expression	-
8	Yale Face Database B	5850	10	Illumination, Expression	http://cvc.yale.edu/projects/yalefacesB/yalefacesB.html
Database for Face Detection					
9	BioID Face Database	1521	23	Illumination, Backdrop, Face size	http://www.humanscan.de/support/downloads/facedb.php.
10	MIT CBCL Face Database #1	30000	-	Face and Non Face Images	http://cbcl.mit.edu/cbcl/software-datasets/FaceData.html
Database for Face Expression Analysis					
11	JAFFE Database	213	10	Expression	http://www.kasrl.org/jaffe.html

12	University of Maryland Face Database	250	40	Expression	-

Conclusion and Open Issues

Many interesting studies on facial age classification have providing good understanding on multifaceted problem and further highlighting various challenges associated with the problem. Despite the high level of current interest in gender and age-group classification systems, there is still no system which is able to work accurately in a real world environment. There are many underlying causes that make it difficult. The age range can be roughly estimated by humans from a face image, labeling such a large data set is very time consuming. Furthermore, there is the possibility of incorrect labeling due to the subjective nature of the observer, the quality of the face images, the viewpoint, scenery, familiarity and the fact that there are people whose looks defy their age. The geometry-based approach is used to classify age-groups is robust against pose and orientation changes. However, the real-world applications are considered, it is difficult to locate facial features due to several corruptions such as illumination, noise and occlusion. The geometry-based approaches need high-resolution images in order to extract the precise positions of facial features such as eyebrows, nose, wrinkles, etc.

Our survey provides a detailed description of many different approaches, although, a comparative analysis of existing techniques is tabulated in table 2.

Table 2: Facial Age Classification algorithms and Features

Sl.No	Authors	Year	Techniques Used	Database / Size	Performance	Classification Types
1	Y. H. Kwon and N. da Vitoria Lobo [5]	1999	Geometrical Classification /Feature Based	Facial Images / 47 Images	68%	Babies, Adults, Senior Adults
2	Andreas Lanitis	2004	Subspace based	FG-NET Aging Database	Age Estimation Error 3.64%	Facial Aging
3	N. Ramanathan, R. Chellappa	2006	Model Based	Passport Database/ Private Datasets	-	Result are reported with Age Transformation and Non-Transformation
4	Gudong Guo, Yun Fu,Charles R. Dyer, Thomas S. Huang	2007	Regression Model	FG-NET Aging Database	90%	Aging Estimation
5	D.Kalamani, P.Balasubramani[19]	2012	Appearance Based Model	-	95%	Aging Estimation
6	Andreas Lanitis	2004	Active Appearance Based Model	FG-NET Aging Database	Better Result	Ranking Model

From reports tabulated above we observe that, Aging estimation is not a standard classification problem but it is multi-class classification problem or regression problem. The study shows the aging estimation must consist of image representation and a technique to aging estimation. In estimation process it's found that geometric model and feature based model are the two dominant approaches. Using geometric model for aging classification must be accompanied with high quality images for better results [19]. Feature based approaches are alternative to geometric models. Anthropometric model, Aging subspace model, Regression model, Appearance model, Active appearance model are the techniques that use facial features to drive aging estimation. Table 2 shows us the performance assessment of various techniques with given dataset. The study of various approaches and techniques gave us a good understanding and also show that various difficulties associated with age estimation problem. Techniques and Dataset alone may not produce high quality aging estimation process. The quality of the image, posture and illumination variation all these factor also having significant influence in result derive process. Apart from these image attributes ethnicity, gender, age group also the factors that affects age estimation process.

Some of observations on future work on facial age estimation are listed below

- Aging estimation algorithms are doing tremendous job in classifying facial image in to specific age groups (child, adults, and senior adults). Facial images with small age separation are very hard to differentiate, in such cases an active learning system must be used to differentiate age groups.
- In our study it is also observed that single still images / Mug-shot images are experimented for age classification process. It may be further extended to group images.

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