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Survey on Age Invariant Facial Recognition

Aman Kumar[1], Aditya Vardhan Srivastava[2] and Pavan Singh Yadav[3]

[1,2,3]*Department Of Computer Science & Engineering Galgotias College Of Engineering And Technology Greater Noida*

Abstract—*The research in age-related face recognition has gained a lot of prominence lately due to the challenging problems of human face aging processes and strong demand of robust face recognition system across ages. Such face recognition systems are crucial in practical applications that need the compensation of age, e.g. missing children identification or passport verification, where there is a significant age difference between probe and gallery images.*

This paper surveys the different models and the algorithms used for age invariant facial recognition that effectively matches faces of a person irrespective of their age. Here we consider two models, first is the generative model that utilizes global features based approaches and second is the discriminative model that uses local features based approaches and is considered better in performance compared to generative model.The discriminative approach addresses the face aging problem in a more direct way without relying on generative aging model.

The discriminative model is used in many algorithms like, SIFT (Scale Invariant Feature Transform), PCA (Principle Component Analysis), MFDA (Multi Feature Discriminant Analysis) and others.

Keywords: *Biometrics, face recognition, Discriminative Approach, Generative Approach*

1. INTRODUCTION

In today's networked world, the need to maintain the security of information is becoming both increasingly important and difficult. The conventional access control systems do not grant access by who we are but by what we have, like ID cards, keys, passwords or PIN numbers, which do not define the person.Face recognition is a biometric system used to identify or verify a person from a digital image or a video frame from a video source. Face recognition system can be generally classified in two groups depending on whether they make use of static images or of video.

Face recognition is a biometric approach that employs automated methods to verify or recognize the identity of a living person based on his/her physiological characteristics. Face recognition is a passive method which extracts the identity of a person in a friendly way .To qualify any biological measurement as biometric, the permanence property should be satisfied. The permanence property is the one according to which the biometric should not vary over a period of time. The aging of a person brings about a change in shape and texture of the face. The aging is a very complex process which depends on many factors like gene pattern, lifestyle, stress, environmental conditions etc. to name a few.

Automatic face recognition is an important yet challenging task due to aging variations, intra-user variations (pose, illumination, expression) and inter-user similarity. Most of the face recognition studies that have addressed the aging problem are focused on age estimation or aging simulation. Designing an appropriate feature representation and an effective matching framework for age invariant face recognition remains an open problem. To address the above mentioned problems a discriminative model has been proposed and major differences between previously used generative model and currently used discriminative model have been identified.

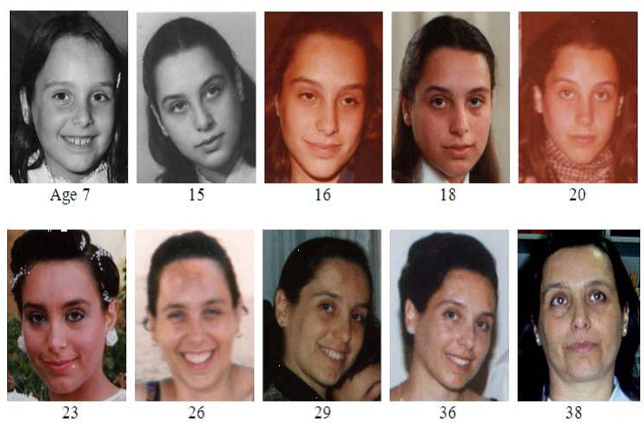

Fig. 1: Example images showing intra-subject variations (e.g., pose, illumination, expression, and aging) for one of the subjects in the FG-NET database[3]

2. LITERATURE SURVEY

Face Recognition Systems that are Age invariant were not widely studied earlier because of the lack of suitable databases, but the recent advent of FGNET and MORPH databases have made this area available for wide research field.

N Ramanathan and R Chellappa [7] presented a Bayesian age-difference classifier that identifies the age Separation between a pair of face images of an individual. While the method presented in this paper is suitable to handle age progression in adult face images, since it does not account for shape variations in faces, it is not effective for handling age progression in face images of children.

H Ling and S Soatto et al [6] proposed a robust face descriptor, the gradient orientation pyramid, for face verification tasks across ages. Compared to previously used descriptors such as image intensity, the new descriptor is more robust and performs well on face images with large age differences. In addition, the pyramid technique enables the descriptor to capture hierarchical facial information.

N R Syambas and U H Purwanto [1] focused on development of image pre- processing factors like contrast, Brightness, Sharpness in the Recognition System for improved recognition accuracy.

G Mahalingam and C Kambhamettu [8] presented a graph based image representationand an aging model constructed using GMMfor each individual to model their age variations mainly in shape and texture. A two stage approach for recognition has been proposed in which a simple deterministic algorithm that exploits the topology of the graphs is proposed for efficient graph matching between the probe image and the gallery image.

J S Nayak and Indiramma M [4] proposed a novel self-PCA based approach in order to consider distinctiveness of the effects of aging of a person for age invariant face recognition. The region around the eyes is used as the input feature instead of the entire face as it is more stable part of the face.

J S Nayak and Nagarathna N et al [5] proposed this self-PCA based face recognition method to consider the aging effects by constructing the subspace at the individual level.

Z Li and U Park et al [3] proposed a discriminative model to address face matching in the presence of age variation. The scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) serve as the local descriptors. Since both SIFT-based local features and MLBP-based local features span a high- dimensional feature space, to avoid the over fitting problem, we develop an algorithm, called multi-feature discriminant analysis (MFDA) to process these two local feature spaces in a unified framework.

3. GENERATIVE MODEL

A generative model considers the formation of the target subject's face to be controlled by a set of hidden parameters. However, the aging process which needs to be modeled is highly complex and there are multiple factors that affect the aging which are subject-specific and depend on the specific age range.

The generative model has simple stages like load input image & perform normal mathematical operation on image .It has less output status in comparison to the discriminative model[3][4]

The generative model has simple stages like load input image & perform normal mathematical operation on image .It has less output status in comparison to the discriminative model[3][4].Most holistic approaches try to generate face aging models and build aging functions to simulate or compensate for the aging process. Active Appearance model (AAM) a statistical face model, to study age estimation problems. In this approach, after AAM parameters are extracted from face image an aging function is built using Genetic Algorithms to optimize the aging function. The probabilistic aging model is individually setup by using Gaussian mixture models (GMMs). In the graph construction algorithm,the feature points of an image and their descriptors are used as vertices and labels correspondingly. There are two steps in their matching process. First, the search space is reduced and the potential individuals are identified effectively by using a maximum a posterior (MAP) for each individual based aging model. Second, a simple deterministic graph matching algorithm is used to exploit the spatial similarity between the graphs.The reason for the low performance of the generative model compared to the proposed discriminative model is the automatic landmark point of detector, that is used for generative model.

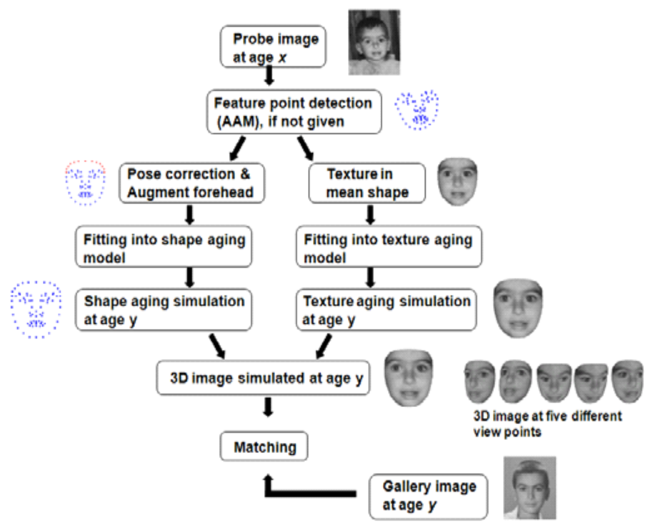

Fig. 2: Schematic of the aging simulation process from age x to age y[3]

3.1 Drawback of Generative model

It has following drawbacks:

- The available face aging databases are usually collected from scanned images in different poses, illumination and expression. Meanwhile most face modeling methods require having face images with frontal pose, normal illumination and neutral expression to get the best fit results.
- In order to have an exact model to represent the aging process, systems have to use a huge number of training images that are usually inefficient for the currently limited face aging databases.
- Forensic scientists proved that human face aging strongly depends on ethnicity and genders Although human faces

have the same general manner when aging, each ethnic and gender group has distinct characteristics in face aging. Therefore, it is insufficient to assume that similar faces age in similar ways for each and every individual

4. DISCRIMINATIVE MODEL[3]

In order to overcome the limitations of generative model, discriminative model was proposed which extracted discriminative local features that are distinct for every subject. Compared to the global feature based approaches, the local features inherently possess spatial locality and orientation selectivity.These properties allow the local feature representations to be robust to aging, illumination, and expression variations. The face recognition algorithms used in this model are Scale Invariant Feature Transform (SIFT), multi scale local binary pattern (MLBP), multi feature discriminant analysis (MFDA) and Principal Component Analysis (PCA). Every algorithm has its own advantage. Compared to the global appearance features, local features have been shown to be more effective in representing face images at diverse scales and orientations and robust to geometric distortions and illumination variations.The local image descriptor-based technique for face representation are SIFT and MLBP.The MFDA is an extension and improvement of the LDA using multiple features combined with two different random sampling methods in feature and sample space. By random sampling the training set as well as the feature space, multiple LDA-based classifiers are constructed and then combined to generate a robust decision via a fusion rule.

4.1 Densely Sampled Local Feature Description[3]

The whole face image is divided into a set of overlapping patches and then the selected local image descriptors is applied to each patch. The extracted features from these patches are concatenated together to form a feature vector with large dimensionality for further analysis. The SIFT feature descriptor quantizes both the spatial location and orientation of image gradient within an $s \times s$sized image patch, and computes a histogram in which each bin corresponds to a combination of specific spatial location and gradient orientation. The accumulation of the histogram bins is weighted by the gradient magnitude and a Gaussian decay function.SIFT feature representation consists of two main parts: key point extraction, and feature descriptors.Densely sample the SIFT feature descriptors from the entire facial image instead of only at a relatively small number of extracted key points.

4.2 Multi-Feature Discriminant Analysis (MFDA)[3]

The MFDA is proposed specifically for handling multiple feature sets with large dimensionality and with different scales and measurements. There are two kinds of local features (SIFT and MLBP), each with two different feature sets corresponding to two different patch sizes. In order to effectively handle these large numbers of features for enhanced performance, we need to overcome two problems: 1) different incompatibility in scale and measurement and 2) overfitting problem. The MFDA algorithm is not developed only to solve the traditional dimensionality reduction problem. In MFDA, different kinds of features are broken into slices and then scaled by PCA normalization, and the overfitting problem is solved by the random sampling.

The use of the bagging technique in the MFDA differs from the traditional random sampling based models. Instead of using the Bagging to randomly sample data within each class or randomly select a subset of classes, the MFDA uses bagging to choose a subset of specific inter-class sample pairs that are close to the classification boundary (in the projected subspace rather than the original feature space) for the construction of the between-class scatter matrix. Therefore, it is not completely random. The reason for adopting such a strategy is due to the fact that the number of inter-class sample pairs is very large, and not all the sample pairs contribute to the learning of discriminative model. Hence it is reasonable to choose a subset of “specific” inter-class sample pairs near the classification boundary as candidates to construct the between-class scatter matrix.

By integrating the MFDA with the densely sampled local feature descriptors, the resulting discriminative model is well suited for age invariant face recognition problem due to the following reasons: (i) the densely sampled local feature description scheme is both an extension and a combination of the SIFT and MLBP. Therefore, it is expected to inherit the discriminative properties of these local description schemes, and furthermore have the capability in extracting age invariant features such as the distribution of edge direction in the face. (ii) MFDA has the capability to effectively combine the rich information conveyed by densely sampled SIFT and MLBP descriptors, which are complementary to some extent.

4.3 Principal Component Analysis (PCA)

PCA involves a mathematical procedure that transforms a number of possibly correlated variables into a number of uncorrelated variables called principal components, related to the original variables by an orthogonal transformation. This transformation is defined in such a way that the first principal component has as high a variance as possible (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, it is also named the discrete Karhunen–Loève transform (KLT), the Hotelling transform or proper orthogonal decomposition (POD).

The major advantage of PCA is that the eigenface approach helps reducing the size of the database required for recognition of a test image. The trained images are not stored as raw images rather they are stored as their weights which are found out projecting each and every trained image to the set of eigenfaces obtained.

5. COMPARISON

Table 1: Comparison of Models

Discriminative Model	Generative Model
• Considers multiple factors affecting the aging process depending on person and specific age range. • Multi class recognition problem • Densely sampled local feature description for feature representation, and further develops the MFDA for classification. • Local features based approach	• Considers the formation of the target subject's face to be controlled by a set of hidden parameters • Binary recognition problem • Gradient orientation pyramid (GOP) for feature representation, followed by the support vector machine classifier for verification • Global features based approach

6. CONCLUSION AND FUTURE WORK

Survey of both models show that discriminative model is more advantageous than generative model. Discriminative model addresses the face aging problem in a more direct way. This model does not require training set of subjects that differ only in their age with minimal variations in illumination and pose, which is often a requirement to build generative aging model. Patch based local representation scheme is used to represent each face and multi feature discriminant analysis (MFDA) is used to refine feature space for enhanced recognition performance & also to overcome the large feature dimensionality problem.

Facial aging is a challenging problem that will require continued efforts to further improve the recognition performance. Future work in this area would involve improving the fusion framework of both generative and discriminative models for enhanced performance and also look for a method that is more tolerant to pose changes.

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