

A Novel Method for Age Invariant Face Recognition

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Abstract:- Security and authorization of person is a crucial part of any industry or organization. There are many techniques available in the industry. Techniques are Password management system, finger print, signature matching etc., one of them is face recognition system. It has received substantial attention from researchers in various fields of science such as biometrics and image processing and Face Recognition system. Many researches in face recognition have been dealing with the challenge of the great variability in head pose, lighting intensity and direction, facial expression, identical twins. One of them is aging face recognition is a challenging task due to the existence of a high degree of correlation in overall facial appearance. In this paper, a face recognition system using Principal Component Analysis (PCA) and deep age face verification (DAFV).

I. INTRODUCTION

There have been very few datasets for the cross-age face recognition research. FG-NET [12], MORPH [28] and CACD [7] databases are the most widely used face databases, which serve as evaluation benchmarks for cross-age face recognition methods [27], [24], [37]. The FG-NET database contains only 1002 images of 82 subjects from age 0 to 69. The relatively small size of the database makes it inappropriate for the real applications. The MORPH database contains two subsets: MORPH album 1 and MORPH album 2. MORPH album 1 contains 1690 images of 625 subjects, and MORPH album 2 contains 15204 images of 4039 subjects. Cross-Age Celebrity Dataset (CACD) is the largest publicly available cross-age face dataset. It contains more than 160 K images of 2K celebrities with age ranging from 16 to 62. The photos in this dataset are collected from the Internet within the range of ten years. However, each subject in the MORPH and CACD database only has images with a small age gap, which makes it inappropriate for modeling the aging process for aging face recognition with large age gaps.

II. RELATED WORK

The research literature on cross-age face recognition is also quite limited over the past decades. Geng et al. [12] modeled the face aging patterns. The face aging pattern is defined as a sequence of face images from the same person sorted in the time order. A principal component space of aging patterns is constructed to model the correlation of faces from different age groups. The faces at different ages of the testing face can be reconstructed by projecting the testing face into the

subspace. Park et al. [27] proposed a 3D aging model, which can capture the aging pattern in the 3D domain. They first converted 2D images into 3D ones by a 3D morphable model [6], and then the facial shape and texture changes are modeled separately in the Principal Component Analysis (PCA) [20] subspace. The missing samples in the training set will be generated by interpolating from the samples of the nearest ages. Wu et al. [35] used a parametric craniofacial growth model to model the facial shape change. These methods can model the aging process of the face shape or texture, but are weak in the discriminative capacity. Li et al. [24] proposed a discriminative model for age-invariant face recognition. They used scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) as local descriptors. To avoid overfitting, multi-feature discriminant analysis (MFDA) was proposed to process the two local feature spaces in a unified framework. It focused on highly discriminative features but failed to model the aging process. With the help of deep learning methods, our proposed framework can not only model and synthesize the aging process, but also learn discriminative features to achieve high performance.

There have been many works exploiting deep learning technology for face analysis/recognition problem. Based on deep belief networks, Luo et al. [25] propose a novel face parse, which can hierarchically parse faces into parts, components and pixel-wise labels. Taigman et al. [33] and Sun et al. [30], [29] use convolutional neural networks (CNN) [21] based methods for face verification problem.

The performance of their works already reaches or surpasses human's performance on the widely used labeled

face in the wild (LFW) dataset [19]. Zhu et al.[36] propose a novel multi-view perception network (MVP), which can reconstruct a full spectrum of views based on a single 2D face. However, all these works have not taken cross-age face verification problem into consideration, which is the main problem we want to handle in our work.

III. DEEP AGING FACE VERIFICATION

A. Framework Overview

Our proposed whole framework for cross-age face verification includes the following steps.

- ◆ Preprocessing: shape and texture separation. Faces are preprocessed to extract shape and shape-free texture.
- ◆ Aging pattern synthesis module. The deep aging-aware de-noising auto-encoder (-DAE) is learned to synthesize the faces at all the age groups for the input face.
- ◆ Aging face verification module. Given aging pattern pair as input, the parallel convolutional neural network is exploited to learn a discriminative space for the verification task.

Both shape and texture of a face contain important information about human age and identity. The cranial size of a face increases quickly as a person grows until 19 years old. After that, the facial texture change becomes the dominant factor for human aging [2]. Wrinkles are deepened at the sides of the eyes, and freckles and aging spots occur on the face skin. However, shape and texture correlate with each other deeply on the face, and are also influenced by other factors, such as pose and illumination. This phenomenon makes cross-age face verification an even more challenging problem. Based on the above observations, we extract shape and texture from the faces and model them separately. 68 face landmark points are located by the OMRON face alignment algorithm. Faces are aligned according to the centers of two eyes and that of the mouth. The shape information is represented by the normalized coordinates of landmark points on the aligned faces.

To extract shape-free texture, we first calculate the mean shape of all the training images from the dataset. Delaunay triangulation [11] is computed on the mean face and each face image in the dataset to obtain 111 triangles. Piecewise linear after piecewise linear affine transformation, which represents affine transformation [14] is applied within the corresponding triangles between the face image and the mean face to obtain the warped face. Fig. 4 shows the shape-free texture extraction process. Fig.

4(a) is the original face image. Fig. 4(b) shows the detected 68 landmark points. The extracted 111 triangles are shown in Fig. 4(c). Fig. 4(d) illustrates the warped face after piecewise linear affine transformation, which represents the shape-free texture.

B. Preprocessing: Shape and Texture Separation

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C. Aging Pattern Synthesis Module

1) Motivations: Facial appearance (shape and texture) changes dramatically along with the human aging process, which poses a great challenge to current face verification systems. For example, if we directly compare two face images of the same person, one for the childhood and the other for the adult, due to the changes in face shape and texture over such a large time span caused by the environment, genes, and other social factors, the similarity between the two faces in the feature space may be low. Most current face recognition systems may fail in such a case. Thus, modeling the face appearance change over the time is a necessary step for cross-age face recognition. Unlike other factors such as gender or facial expression, face aging has its own characteristics. First of all, human aging is personalized. One's face appearance is determined by mainly two aspects: internal factors, i.e., genes, and external factors, such as one's living environment, lifestyle, etc. Genes determine the initial appearance of a person. As the person grows up, many external factors may impose their influence on what he/she looks like. For example, a man who has an unhealthy diet tends to have a fat face. Secondly, face aging is an irreversible sequential

process. Every person, if no deathly accident or disease occurs, experiences the growing process from childhood, youth to adult and old age, in a temporal order. No one can go through the process the other way around. It is slow with decades of time, but irreversible.

Based on the characteristics, the face appearance change of each subject should be considered as a function of both identity and age. Each image in the cross-age face dataset should have and the age label. two labels: the identity label This is the difference between the ordinary face verification problem and the cross-age face verification problem. For the ordinary face verification problem, given two input faces and , the system verifies whether equals. No age information is considered in the ordinary face system. In the cross-age face verification system, given two input faces at a date. Then it will work based on algorithm.

Algorithm:

- 1: **Inputs:** The face images and image pairs in the Training set.
- 2: **Outputs:** The learned parameters of the a2 -DAEs and the CNNs. Train the a2-DAEs:
- 3: Pretrain the encoding layers of a2 -DAE with M0b
- 4: for I = 1 to 4 do
- 5: Pretrain the decoding layers on the i-th branch of a 2 -DAE with Mib
- 6: end for
- 7: Train the a2-DAE model M0a with the whole training set.
- 8: for t = 1 to T do
- 9: Train the t-th a2-DAE model Mtb
- 10: Obtain the synthesized aging patterns on the t-th training subset.
- 11: end for
- 12: Obtain the synthesized aging patterns of all the training subsets. Train the parallel CNNs:
- 13: Train the CNN Mtb on the original images.
- 14: for i = 1 to 4 do
- 15: Train the i-th CNN Mi5 on the constructed faces of the i-th age group.
- 16: end for
- 17: Jointly fine-tune the CNNs { Mi5 1 i=0.....4} obtain the CNN Ms.

IV. RESULT

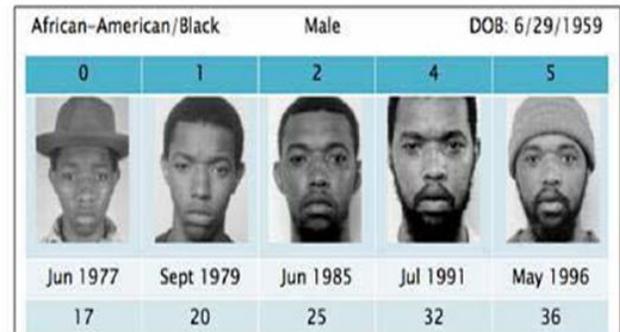


Fig.1 a

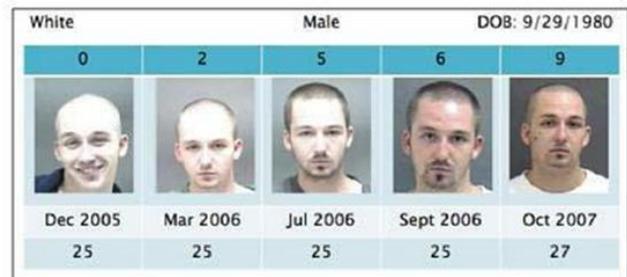


Fig.1.b

Fig. 1. Sample of face images from (a) MORPH-album 1, (b) MORPHalbum 2

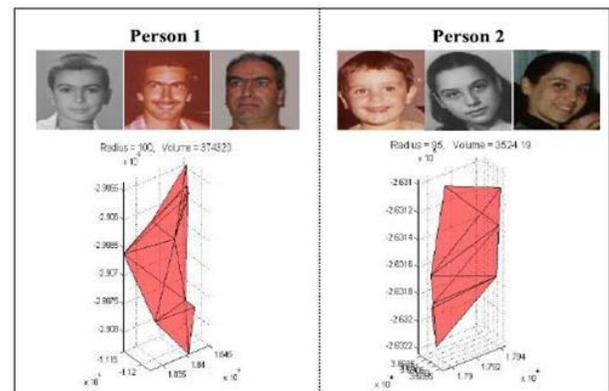


Fig. 2. a shapes of two different individuals computed and stored as prototypes in the FGNET gallery.

V.CONCLUSION AND FUTURE WORK

In this work, we have developed a novel framework DAFV for aging face verification with large gaps. Two modules, aging pattern synthesis and aging face verification, are included in this framework. In the aging pattern synthesis module, we have proposed a novel deep

aging-aware denoising auto-encoder (-DAE) to synthesize the faces of four age groups for the input face of an arbitrary age. In the aging face verification module, given a face pair as the input, each pair of synthesized faces of the same age group

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