Review on Face Recognition across Age Progression

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Abstract: Face recognition is one of the most successful applications for many years of emergent research on image analysis. Face recognition is mainly recommended for identity authentication or identification, passport photo verification, image retrieval, surveillance, missing person identification and security access control etc. Face recognition across aging is a challenging task which poses theoretical and practical challenges to the research community since facial aging has high impact on facial recognition task. To overcome the problems of human face aging, there is a need of reliable and robust face recognition system across ages. Human faces which will undergo considerable amount of variations with aging have been studied. This paper discusses about multiple interesting studies that have been performed on this topic. We also present the performance analysis of various methods for face recognition across age progression.

Keywords: Face Recognition, Age Progression, Facial Aging

I. INTRODUCTION

Face recognition is one of the most popular biometric methods used for recognizing and authenticating each individual. The word biometrics originates from Greek language and derived from the words bio (life) and metric (to measure). Biometrics is the science of identifying or verifying the identity of a person based on physiological or behavioural features. Face recognition is defined as the biometric identification by scanning a person’s face and matching it against a dataset of known faces. It is mainly used in security control systems and can be compared to other biometrics such as fingerprint, retina or iris recognition systems.

1.1. Components of Face Recognition System

The input of a face recognition system is always an image or video stream. The output is an identification or verification of the subject or subjects that appear in the image or video. The figure below shows the generic structure of a face recognition system. The face recognition procedure has 3 steps: Face Detection, Feature Extraction and Face recognition [16].

Face detection is defined as the process of extracting faces from scenes. So, the system positively identifies a certain image region as a face. It is also defined as determine position of single face in a given image.

Feature Extraction is the process of obtaining relevant facial features from the original data. These features could be certain face regions, variations, angles or measures, which can be human relevant (e.g. eye spacing) or not.

In Face recognition step system recognizes the face. In an identification task, the system would report an identity from the database. This step involves a comparison method, a classification algorithm and accuracy measure.
1.2. Face Recognition across Age Progression

Human faces undergo a lot of change in appearance over time or as they age. The variations caused by aging differ with respect to age and are influenced by many factors. Precisely, from childhood to adulthood facial variations are more prominent. Later, during the adulthood, wrinkles and pigmentation of the skin can be observed.

There have been many works related to the facial recognition algorithms and systems. Also, the efforts are being carried out to improve the accuracy and efficiency of these algorithms and systems. Various artefacts affecting the performance of face recognition system such as pose variations, facial expressions and illumination variations have been studied by the researchers.

Aging is another factor influencing the performance of the facial recognition system apart from the above mentioned factors. Hence, there is a need to consider aging also as an important factor while building a performance efficient face recognition system. This feature will be helpful in the context of identifying the missing persons, passport verification or renewal where there is need to cross check the old and new photographs of the same person [4].

The rest of the paper is organized as follows, Section 2 presents a brief survey on many methods for face recognition across age progression. Section 3 presents performance measure of the methods that are described in section 2. Section 4 presents the facial aging databases which are used in studies of facial aging problem and the last section presents the conclusion.

II. LITERATURE SURVEY

a) Face verification of age separated images under the influence of internal and external factors [1]:

Mahalingam and Kambhamettu studied the task of face verification with age variations under the influence of internal and external factors. Face image is holistically represented using the hierarchical local binary pattern feature (HLBP) descriptor for robust face representation across age. The effective representation by HLBP across minimal age variations, illumination, and minimal pose variations provides a discriminative representation of the face image across age. They proposed an AdaBoost classifier for identifying intrapersonal and extra personal image pairs across aging. The combination of LBP at each level of the Gaussian pyramid formulated for each face image is considered as spatial information.

b) 3D facial Aging Model [2]:

Park et al. proposed a 3D facial aging model and simulation method for age-invariant face recognition. The goal is to improve the performance of face recognition and matching scheme that is used to compensate for the age variations. The proposed model adapts view invariant 3D face models to the given face aging database of 2D face models. The intent of the method is based on the fact that exact craniofacial aging can be developed only in 3D. The benefit of using this model is it reduces the variations due to pose and lighting.

c) NMF algorithm with sparseness constraints [3]:

Du et al. proposed a method called Non-negative matrix factorization (NMF) with sparseness constraints for simulation of facial aging. In the proposed method, initially an advanced prototyping
method was used to perform the task of human face aging, which wish to consolidate sparseness constrained NMF to extract facial image texture features and decide which part of the factorized matrix to be kept sparse, the coefficients H or the basis vectors W, hence we could obtain more satisfied result. Later, the accuracy of face recognition is improved through the method of simulating virtual aged facial images based on the proposed aging method.

\textbf{d) Facial Aging in Adults [4]:}

Ramanathan and Chellappa proposed a model called \textit{Modeling shape and textural variations in aging adult faces}. The method comprises two steps towards modelling facial aging in adults. The model contains two types namely, a shape variation model and a texture variation model. Initially, we develop a shape transformation model which is formulated as a physically-based parametric muscle model. The model accounts for the physical properties and geometric orientations of the individual facial muscles. Facial muscles can be identified in one of three types namely, (i) Linear muscles (ii) Sheet muscles (iii) Sphincter muscles. The second model called texture variation model was designed to characterize facial wrinkles in the forehead, nasolabial region etc.

In the absence of age-based anthropometric measurements extracted on adults across ages, facial growth data was collected by extracting facial features on the passport database. Such facial growth data was collected on five different age groups 21-30 yrs, 31-40 yrs, 41-50 yrs, 51-60 yrs and 61-70 yrs. The facial growth data collected in this manner was found to be effective in characterizing facial growth based on age, gender, ethnicity etc. and further during instances when individuals gain or lose weight.

\textbf{e) Graph matching [5]:}

Mahalingam and Kambhamettu proposed a method called \textit{Age invariant face recognition using graph matching}. The graph based face representation contains information related to appearance and geometry of facial feature points. For each individual a model of age variations mainly in shape and texture is constructed by using an aging model. For effectively extracting the facial feature points a modified Local Feature Analysis is used that uses Fisher score to extract the facial feature points. To compute a feature descriptor for each facial feature point, Uniform Local Binary Pattern (LBP) operator was applied to each facial feature point and was used in graph representation. A two stage method for recognition is proposed, in which the first stage involves a Maximum a Posteriori solution based on PCA factorization for pruning the search space and selecting very few candidate model sets. In the second stage, a simple deterministic algorithm that exploits the topology of the graph is used for matching between the probe image and gallery image.

\textbf{f) Bayesian Framework [6]:}

Ramanathan and Chellappa proposed an approach ‘Face verification across age progression’ for face recognition. The proposed method estimates the age separation between a pair of face images of an individual. The study on this method consists of four categories namely, 1-2 years, 3-4 years, 5-7 years and 8-9 years. They collected difference images from pairs of age separated face images from the respective categories and created an intra-personal subspace for each category. They proposed a Bayesian age-difference classifier which is built on a probabilistic eigen faces framework to recognize face across aging.
g) Aging Pattern Subspace [7]:

Geng et al. proposed the ‘Automatic age estimation based on facial aging patterns’ approach to perform age estimation from face images. The author proposed AGES method for automatic age estimation. ‘Aging pattern’ is defined as a sequence of individual face images ordered in time. The intent of the AGES method is to characterize the temporal nature of the underlying data and hence capture the appearance changes in face across aging. Collecting a complete aging pattern for each person is a difficult task, hence they developed the ‘aging pattern subspace’ drawing inspiration from methods that develop an eigen space by making use of incomplete data (data with missing features). After developing the subspace, the age of a previously unseen face and the aging pattern is determined by the projection in the subspace that best reconstructs the face.

h) Bacteria Foraging Fusion [8]:

The bacteria foraging fusion algorithm proposed by Yadav et al. improves the performance of face recognition. The bacteria foraging fusion algorithm combines the Local Binary Pattern (LBP) features of both local and global regions at match score level which mitigates the variations of facial changes by aging.

i) Periocular Biometrics [9]:

Periocular Biometrics framework was proposed by Juefei-Xu et al. which depicts utilizing periocular region for face recognition in the context of invariant age. Initially, performed pre-processing schemes like pose correction, illumination and periocular region normalization to obtain age invariant features. Then, on these pre-processed periocular region authors applied robust Walsh-Hadamard transform encoded local binary patterns (WLBP). At last, they built subspaces on WLBP featured periocular images by using unsupervised discriminant projection (UDP).

j) Discriminative model [10]:

The approach used in this work is based on Discriminative Model for Age Invariant Face Recognition by Li et al. Here author has used scale invariant feature transform (SIFT) and multi-scale local binary patterns (MLBP) as the local descriptors and represented each face by designing a densely sampled local feature description scheme. They developed an algorithm called multi-feature discriminant analysis (MFDA) to process both SIFT-based local features and MLBP-based local features in a unified framework to avoid the over fitting problem caused by these two local features. Multiple LDA based classifiers are constructed and combined by sampling both training set and feature space and generated a robust decision via a fusion rule.

k) Local descriptors in application to the aging problem [11]:

Local descriptor method was evaluated by Bereta et al. for face recognition across age progression. The aim of the study was to assess and compare the accuracy of the recent local descriptors along with their application to age invariant face recognition. The verification was conducted on following descriptors: local binary pattern (LBP), improved LBP (ILBP), centre-symmetric LBP (CSLBP), differential local ternary pattern (DLTP), three patch LBP (TPLBP), multi-scale block LBP (MLBHP), simplified form of Weber local descriptor (WLD), local XOR pattern (LXP), local Gabor phase binary pattern (LGPBP), local Gabor XOR pattern (LGXP). Also, the first seven of above descriptors were tested in application to Gabor magnitude images.
Author has described these descriptors as standalone entities not combined with Gabor wavelets, where the descriptors are applied to Gabor magnitude and Gabor phase images.

III. PERFORMANCE ANALYSIS AND EXPERIMENTAL RESULTS

a) Face verification of age separated images under the influence of internal and external factors [1]:

Experiments were conducted for FG-NET and MORPH database by considering several factors which affect the performance of a face verification system. The results on the FG-NET and MORPH aging datasets shows that the performance of the proposed framework is more robust to both adult and children images. The result shows that as the age difference between the image pair increases the accuracy of face verification decreases. The effects of internal (age gap, gender, and ethnicity) and external (pose, expressions, facial hair, and glasses) factors which affect the performance of face verification was also analyzed.

b) 3D facial Aging Model [2]:

Experimental results are evaluated using a commercial face recognition engine called FaceVACS and showed the improvements in performance of face recognition by using FG-NET, MORPH, and BROWNS aging databases. The proposed method is able to handle both developmental and adult face aging effects.

| Database(#subjects, #images) in probe and gallery | Recognition Accuracy |
|--------------------------------------------------|-----------------------|
| FG-NET (82,1002)                                 | 37.4%                 |
| MORPH Album 1 (612, 612)                         | 66.4%                 |
| MORPH Album 2 (10000, 20000)                     | 79.8%                 |

c) NMF algorithm with sparseness constraints [3]:

Apart from lighting, gesture and expression, aging is also one of the important factor which affects face recognition. Aging effects on teenagers facial growth and face recognition rate can be improved after adding additional virtual samples by aging simulation. Experimental results shows that Non-negative matrix factorization (NMF) with coefficient H sparse performs better than PCA method in texture aging and also improves the accuracy of face recognition across age progression.

| Database | Recognition Accuracy |
|----------|----------------------|
| FG-NET   | age groups < =18     |
|          | 39.2%                |
|          | age groups > 18      |
|          | 58.7%                |

d) Facial Aging in Adults [4]:

The experiments were conducted on a database that consists of 260 age separated image pairs of adults for face recognition across age progression. The collected image pairs were compiled from both the Passport database and FG-NET database. Authors have used Principal Component Analysis.
(PCA) to perform face recognition across ages under the following three setting: (i) No transformation in shape and texture (ii) Performing shape transformation (iii) Performing shape and textural transformation.

Below table reports the Rank-1 recognition accuracy under the three setting. The experimental results indicate the importance of transforming shape and texture during face recognition across ages.

| Experimental Setting                  | Recognition Accuracy |
|---------------------------------------|----------------------|
| No transformations                    | 38%                  |
| Shape transformations                 | 41%                  |
| Shape and Texture transformations     | 51%                  |

Table 3. Face recognition across ages

**e) Graph matching [5]:**

The experimental results were evaluated on FG-NET database. The proposed algorithm results shows that the accuracy of age invariant face recognition is achieved by combining both aging model and the graph representation.

**f) Bayesian Framework [6]:**

The proposed method is more useful in renewal of passport. In renewal of passport, age difference between the image pairs is known apriori. The age difference classifier establishes the identity between the image pairs provided a pair of age separated face images of an individual. Later the classifier further classifies them to their corresponding age difference category. The study on facial aging using Bayesian framework provides a good understanding of the problem and challenges linked with the problem.

Table 4. Rank-one identification accuracy

| Database(#subjects, #images) in probe and gallery | Recognition Accuracy |
|---------------------------------------------------|----------------------|
| Public domain                                     | 15.0%                |
| Private database (109,109)                         |                      |

**g) Aging Pattern Subspace [7]:**

Table below reports the Rank-1 identification accuracy for FG-NET database.

Table 5. Rank-one identification accuracy

| Database(#subjects, #images) in probe and gallery | Recognition Accuracy |
|---------------------------------------------------|----------------------|
| FG-NET (10,10)                                    | 38.1%                |

**h) Bacteria Foraging Fusion [8]:**

In this paper, the experimental results were obtained using the FG-Net and IIITDelhi face aging databases. The IIITDelhi database which was considered for experiment consists of over 2600 age separated labeled face images of 102 individuals with numerous variations in the faces like illumination variation, pose variations and presence of eye glasses etc.
Table 6. Rank-1 accuracy obtained by using the proposed algorithm on the IIITDelhi and FG-Net databases.

| Database | Oldest Image as Probe | Youngest Image as Probe |
|----------|-----------------------|-------------------------|
|          | IIITDelhi | FG-Net | IIITDelhi | FG-Net |
| Recognition Accuracy | 54.3% | 64.5% | 33.3% | 31.2% |

By observing the above table it is clear that recognizing a person face is more difficult if the youngest image is used as probe compared to using the oldest image as probe. Rank -1 accuracy has achieved 54.3% accuracy in case of oldest image as probe on IIITDelhi database and 64.5% accuracy on FG-Net database.

i) Periocular Biometrics [9]:

The WLBP featured periocular images with subspace modeling using UDP was able to obtain 100% rank-1 identification accuracy rate and 98% VR at 0.1% FAR on FG-NET database.

Table 7. Rank-one identification accuracy for FG-NET Database(#subjects, #images) in probe and gallery

| Database(#subjects, #images) | Recognition Accuracy |
|------------------------------|----------------------|
| FG-NET (82,1002)             | 100%                 |

j) Discriminative model [10]:

Experimental results are presented using two public domain face aging data sets: MORPH and FG-NET to outperform a state of the art commercial face recognition system. The proposed method solves the face aging problem in a direct way not depending upon generative aging model. Since generative aging model depends on the requirement like images with minimal variations in illumination and pose variations. Experiments were conducted using Multi-feature discriminant analysis (MFDA) method to refine the feature space for better performance accuracy and enhanced recognition.

Table 8. Rank-one identification accuracy

| Database(#subjects, #images) in probe and gallery | Recognition Accuracy |
|--------------------------------------------------|----------------------|
| FG-NET (82,82)                                  | 47.50%               |
| MORPH Album 2 (10000, 20000)                    | 83.9%                |

k) Local descriptors in application to the aging problem [11]:

Experimental results are obtained by using local descriptors combined with Gabor magnitude and Multi-scale Block LBP (MBLBP) and achieved highest accuracy. This descriptor is more stable for different age groups and ranks. But, descriptors combined with Gabor phase produce significantly lower recognition accuracy.

The results showed that local descriptors and Gabor wavelets is a powerful tool for face recognition across aging and they need to be supported by the methods for increasing the accuracy of face recognition or reducing the dimensionality of feature description.

From the results it is observed that the recognition accuracy differs with various descriptors. The MBLBP is considered as the best descriptor among the other descriptors not combined with Gabor
images, provided the age difference between the training image and test image are short i.e., between 0 and 5 years, or relatively high, i.e., between 21 and 30 years. The results observed were very poor when using the LBP and its modifications such as TPLBP, CSLBP, and ILBP. The TPLBP is highly robust with respect to short and middle age differences.

IV. FACIAL AGING DATABASES

Lot of databases containing faces have been segregated to support the study of face recognition. The MORPH Database, the FGNET Aging Database and the FERET Database [12] are the three publicly available databases. These databases contain the images with respect to the age.

A. The MORPH Database

The facial images of adults that were taken in different ages are present in the MORPH Database (Craniofacial Longitudinal Morphological Face Database). Organization of the database is as follows: the two columns ‘MORPH Album 1’ and ‘MORPH Album 2’. ‘MORPH Album 1’ include 1690 images of 515 individuals aging in between 15-68 years. ‘MORPH Album 2’ includes 15204 images of nearly 4000 individuals. Along with the face images, meta information that is critical for analysing the age progression, height and weight is also provided by the database [12].

B. FG-NET Aging Database

The Face and Gesture Recognition Research Network (FG-NET) aging database includes 12 pictures of varying ages between 0 and 69, for each of its 82 subjects. Totally there are 1002 colour and grey scale images taken in natural environments. Every image is annotated manually with 68 landmark points. Along with the images, there is a data file for every image, containing type, quality, size of the image and information about the subject such as age, gender, spectacles, hat, moustache, beard and pose. Disadvantage of this database is that the images are not equally distributed over age hence, only few images of persons older than 40 are available [13].

C. FERET Database

The Face Recognition Technology (FERET) program [15] database is one of the largest databases of facial image which is partitioned into development and sequestered portions. The development portion is reserved to researchers and the sequestered portion is dedicated to testers for testing face recognition algorithm. The proposed database is recommended for solving various problems related to face recognition such as illumination variations, pose variations, facial expressions etc., It also contains hundreds of age separated face images of subjects (the age separation amounting to 18 months or more).The FERET database referring to facial aging can also be described as follows [12]:

- Gallery-set: Comprises of 1196 images
- Duplicate I Probe-set: Comprises of 722 images of subjects whose gallery match was taken 0 - 1031 days beforehand.
- Duplicate II Probe-set: Comprises of 234 images of subjects whose gallery match was taken 540 - 1031 days beforehand.

V. CONCLUSION

In this paper we have studied and analysed various interesting methods and algorithms that provides solution to the face recognition across aging problem. The analysis is very much needed in developing robust algorithm for face recognition across age progression. The paper examines how
facial aging impacts the recognition performance and it also examines the performance analysis of some of the methods for face recognition across aging problem. We need a robust methodology which can improve the performance of face recognition across aging in terms of both accuracy and time. Face recognition across aging has many applications such as forensic science, border control, driver's license and passport verification, access control, localization of missing people, etc.

REFERENCES

[1]. G. Mahalingam and C. Kambhamettu. Face verification of age separated images under the influence of internal and external factors. In Image and Vision Computing 30 (2012) 1052–1061.
[2]. U. Park, Y. Tong, and A. K. Jain. Age-invariant face recognition. IEEE TPAMI, 32(5): 947–954, 2010.
[3]. J. Du, C. Zhai, Y. Ye. Face aging simulation and recognition based on NMF algorithm with sparseness constraints. In Neurocomputing 116 (2013) 250–259.
[4]. N. Ramanathan and R. Chellappa, “Modeling shape and textural variations in aging adult faces,” in IEEE International Conference on Automatic Face and Gesture, Amsterdam, Netherlands, 2008.
[5]. G. Mahalingum and C. Kambhamettu. Age invariant face recognition using graph matching. In IEEE BTAS, 2010.
[6]. N. Ramanathan and R. Chellappa, “Face verification across age progression,” in IEEE Conference on Computer Vision and Pattern Recognition, vol. 2, San Diego, U.S.A, June 2005, pp. 462–469.
[7]. X. Geng, Z. H. Zhou, and K. Smith-Miles, “Automatic age estimation based on facial aging patterns,” IEEE Pattern Analysis and Machine Intelligence, vol. 29 (12), pp. 2234–2240, December 2007.
[8]. D. Yadav, M. Vatsa, R. Singh and M. Tistarelli, “Bacteria Foraging Fusion For Face Recognition Across Age Progression,” in IEEE Conference on CVPRW, Portland, Oregon, USA 2013.
[9]. F. Juefei-Xu, K. Luu, M. Savvides, T. D. Bui, and C. Y. Suen. Investigating Age Invariant Face Recognition Based on Periocular Biometrics. IEEE, 2011.
[10]. Z. Li, U. Park, and A. Jain, A discriminative model for age invariant face recognition. IEEE TIFS, 6(3):1028 –1037, 2011.
[11]. M. Bereta, P. Karczmarek, W. Pedrycz, M. Reformat. Local descriptors in application to the aging problem in face recognition. InPatternRecognition 46 (2013)2634–2646.
[12]. N. Ramanathan, R. Chellappa and S. Biswas “Age Progression in Human Faces: A Survey”.
[13]. Fg-net aging database, http://fipa.cs.kit.edu/429.php
[14]. http://www.face-rec.org/databases/
[15]. P. J. Phillips, H. Moon, and P. J. R. S. A. Rizvi, “The FERET database and evaluation procedure for face recognition algorithms,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22(10), pp. 1090–1104,2000.
[16]. PF de Carrera, I. Marqués, Manuel Graña, “Face Recognition Algorithms”, 2010.