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Performance Analysis of Age Invariant Face Recognition Methods

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***Abstract*—** Age Invariant Face Recognition is an emerging research topic in Face Recognition Research Community has many practical applications such as in law enforcement, identifying criminals, passport renewal etc. Facial Aging has not received adequate attention compared to other sources of variations due to pose, lighting, and expression. This paper aims to give a detailed survey of age invariant face recognition. This review covers the techniques that attempt to solve the age invariant problems. This paper also discusses different techniques to extract features and textures of age invariant facial part. Existing problems in age invariant face recognition are covered and possible solutions are suggested in this review. Advantage and disadvantage of each methods and recognition accuracy have been discussed.

***Keywords*— :** Age invariant, face recognition, aging database, Morph, FGNET and Epoch database.

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 whom 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 as shown in Fig.1. Most of the face recognition studies that have addressed the aging problem are focused on age estimation or aging simulation. Designing an suitable feature extraction and an effective classifier structure 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 MORPH database

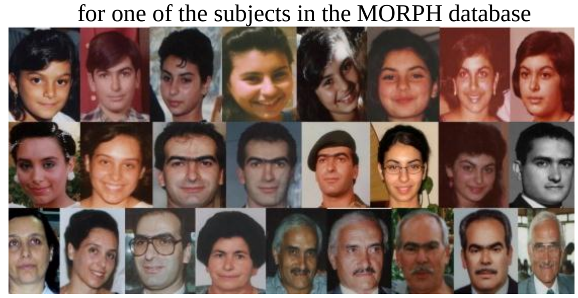

Fig.2. An example of Images from FGNET age database

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II. LITERATURE REVIEW

Age invariant face recognition system were not widely considered earlier because of the lack of suitable databases, but the recent advent of FGNET [22], MORPH [21] and Epoch [23] databases have made this area available for wide research field. The sample images from FGNET and Epoch aging databases are shown in Fig.2 and Fig.4 respectively.

A) Facial Feature Points

Facial feature points are having semantic meaning which are mainly located around facial components such as eyes, mouth, nose and chin (see Fig.3). Facial feature point detection (FFPD) refers to a supervised or semi-supervised process using abundant manually labeled images [1]. FFPD usually starts from a rectangular bounding box returned by face detectors which implies the location of a face. This bounding box can be employed to initialize the positions of facial feature points. Fig.3 shows the fitting of feature points in face. Facial feature points can be reduced to three types: points labeling parts of faces with application-dependent significance, such as the center of an eye or the sharp corners of a boundary; points labeling application-independent elements, such as the highest point on a face in a particular orientation, or curvature extrema (the highest point along the bridge of the nose); and points interpolated from points of the previous two types, such as points along the chin.

Fig. 3. Illustration of an example image with 68 manually labeled points

Fig.4. An example of Images from Epoch age database

According to various application scenarios, different numbers of facial feature points are labeled as, for example, a 17-point model, 29-point model or 68- point model. Whatever the number of points is, these points should cover several frequently-used areas: eyes, nose, and mouth. These areas carry the most important information for both discriminative and generative purposes. Generally speaking, more points indicate richer information, although it is more time-consuming to detect all the points.

B) 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. 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. Gaussian mixture models (GMMs) are used to setup the individual probabilistic aging model. 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 automatic landmark point of detector is the reason for the low performance of the generative model compared to the proposed discriminative model is

C) Discriminative Model

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.

D) Densely Sampled Local Feature Description

The whole face image is divided into a set of overlapping patches and then the selected local image descriptors are

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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 8×8 sized image patch, and computes a histogram in which each bin corresponds to a combination of specific spatial location and gradient orientation.

E) Multi-Feature Discriminant Analysis (MFDA)

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) over fitting 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 over fitting problem is solved by the random sampling. 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.

F) Texture based Methods

Jyothi S et al. [3] proposed a self-Principal Component Analysis (PCA) based method to model the age variations of face.PCA is a face recognition method which uses Karhunen-Loeve transform. Self-PCA based method shows improved recognition rate in comparison with PCA. The recognition rates obtained using PCA and Self-PCA 70%. But for the same test set the recognition rate using PCA reduces to 50%. Diana Sungatullina et al. [6] proposed a discriminative learning method with multiview feature representations, called MDL, to project different types of local features into a latent discriminative subspace where the intraclass variation of each feature is minimized, the interclass variation of each feature and the correlation of different features of the same person are maximized, simultaneously, such that more discriminative information can be boosted for recognition. But we expect different classes (seen and unseen) to be well separated while all the within-class samples collapse to a point.

Djamel Bouchaffra et al. [7] proposed a paper for reducing the dimension of the observed variables through a kernelized radial basis function technique and expressing the latent variables probability distribution in terms of the observed variables. Disclosing the data manifold as a 3-D polyhedron via the α-shape constructor and extracting topological features and classifying a data set using a mixture of multinomial distributions. The benefit of expressing p(x) is invaluable since it allows the estimation of some parameters and the generation of other points in case where face images of the same individual are lacking. However, our methodology can still be improved through the use of a more stable clustering algorithm of the zi vectors. A.Sindhuja et al. [8] proposed Scale Invariant Feature Transform (SIFT) and Multi scale Local Binary Pattern (MLBP) method for feature extraction and o recognize the occluded face images also. Since the extracted features are with high dimensionality new technique called Multi Feature Discriminant Analysis (MFDA) is used to reduce the feature space. Main benefit of MFDA method is recognition of occluded image with various ages. Even though MFDA gives high recognition rate when compared with nearest neighbor method, it contains 3500 classifiers which take longer time to recognize but nearest neighbor method uses only 700 classifiers and results with the recognition accuracy nearer to MFDA method. Felix luefei-Xu et al. [9] proposed a Walsh-Hadamard transform encoded local binary patterns feature on periocular region maintains consistency of the same individual across ages. he WLBP featured periocular images with subspace modeling using UDP was able to obtain 100% rank-1 identification rate and 98% VR at 0. 1 % FAR, a giant leap from by far the best performing algorithm on full face for age invariant face recognition on FG-NET database. Compared to traditional ways of subspace modeling, out novel subspace modeling method has gained significant improvement by building subspaces on WLBP featured image, not on raw pixel intensity.

Junyong Si et al. [10] proposed a PLS (Partial Least Square) model that considers feature changes in a continuously progressive way and we use this model to take advantage of the stable features in a relatively short age period with progressive changes of the features through all ages which ensures the robustness to age variance compared with previous discriminative methods. This method takes advantage of stable features in an age period with progressive changes of the features through all ages. Therefore it can overcome the performance problem with small age gap and noise in previous discriminative methods. Zhifeng Li et al. [1] proposed a discriminative model to address face matching in the presence of age variation. The face is designed by a densely sampled local feature description scheme, in which scale invariant feature transform (SIFT) and multi-scale local binary patterns

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(MLBP) serve as the local descriptors. Compared the performance of the proposed discriminative model with a generative aging model. A fusion of discriminative and generative models further improves the face matching accuracy in the presence of aging.

Gayathri Mahalingam et al. [2] proposed a two-stage method, where the first stage involves a Maximum a Posteriori solution based on PCA factorization to efficiently prune the search space and select very few candidate model sets. A simple deterministic algorithm which exploits the topology of the graphs is used for matching in the second stage. The experimental results on the FGNET database show that the proposed method is robust to age variations and provides better performance than existing techniques. Nana Rachmana Syambas et al. [5] proposed PhotoScape v3.5 software for simulation of image Processing and VeriLook 5.0/MegaMatcher VeriLook 4.0 Algorithm for verification. In verification process, the results of the combination increase the success rate of matching faces by 13.57%, where 96 image pairs successfully matched from a total of 140. Jyothi S. Nayak et al. [3] 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 recognition rate obtained is more promising and more accurate compared to other papers. Chi Nhan Duong et al. [17] proposed a novel generative probabilistic model, named Temporal NonVolume Preserving (TNVP) transformation to model the facial aging process at each stage. Our approach can model any face in the wild provided with only four basic landmark points. It shows advantages not only in capturing the non-linear age related variance in each stage but also producing a smooth synthesis in age progression across faces.

Tianyue Zheng et al. [14] proposed a novel deep face recognition network called age estimation guided convolutional neural network (AE-CNN) to separate the variations caused by aging from the person specific features which are stable. . Considering the fact that directly obtaining person-specific feature is difficult since the feature we get by face recognition task always contains age-related factor, we add age estimation task to obtain age feature and subtract age factor from the whole feature. Yandong Wen et al. [15] proposed a novel deep face recognition framework to learn the age invariant deep face features through a carefully designed CNN model. The effectiveness of deep CNNs in advancing the state-of-the-art of AIFR. Extensive experiments are conducted on several public-domain face aging databases to demonstrate the significant performance improvement of this new model over the state-of-the-art and also experiments were performed on the famous LFW dataset to demonstrate the excellent generalization ability of this new model. Dihong Gong et al. [16] proposed a new maximum entropy feature descriptor (MEFD) that encodes the microstructure of facial images into a set of discrete codes in terms of maximum entropy. By densely sampling the encoded face image, sufficient discriminatory and expressive information can be extracted for further analysis. A new matching method is also developed, called identity factor analysis (IFA), to estimate the probability that two faces have the same underlying identity. Directly applying it on the LFW database cannot fully demonstrate its advantages. Nevertheless, this approach still obtains a good result on the LFW database, only slightly lower than 88.97%.

Amal S Osman Ali et al. [12] proposed a local binary pattern (LBP) texture descriptor to handle texture variations. The results showed that fusing the shape and the texture features set yielded better performance than the individual performance of each feature set. Moreover, the individual verification accuracy for each feature set was improved when they were transformed to a kernel discriminative common vectors presentation. Huiling Zhou et al. [18] proposed canonical correlation analysis to predict the aging of facial features so as to alleviate the effect of age progression on face recognition. The performance of our proposed approach is evaluated based on the FG-Net database, and compared to some existing face recognition algorithms. Experiment results show that our proposed method can achieve a superior performance, when the query and probe face images have a large age difference. Cui Meng et al. [19] proposed a principal component analysis (PCA) to reduce the dimensions of the extracted features. Experimental results on the MORPH database, one of the largest publicly available face dataset containing thousands of longitudinal images are presented. To find the age invariant method for face recognition, the Gabor wavelets, local binary pattern, and gradient orientation pyramid are performed on the designed the database which organized by different age ranges. The comparison results show that all these methods outperform than the raw data in most cases, which represent that they are all helpful to reduce the sensation of the age factor when doing face recognition.

Dihong Gong et al. [11] proposed a Hidden Factor Analysis (HFA) to separate the variation caused by aging from the person-specific features that are stable. This method captures the intuition above through a probabilistic model with two latent factors: an identity factor that is age-invariant and an age factor affected by the aging process. Then, the observed appearance can be modeled as a combination of the components generated based on these factors. Extensive experiments conducted on two public domain face aging datasets convincingly demonstrate the superiority of our HFA model over the state-of-the-art algorithms. Xiaonan Hou et al. [20] proposed PCA and LDA to retain feature robustness to noise and large intra-personal age-variance in face images. Here the original feature to a new space in which the feature is robust to noise and large intra-personal

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variations caused by aging face images. Then further encoding the mapped feature into an age-invariant representation is carried out. After mapping and encoding, the robust and discriminative feature for the specific purpose of age-invariant face recognition is obtained.

Table 1. The Recognition Rate Performance Different Age Invariant Face Recognition on FG-NET database

S.No	Author	Method	Database	Recognition Rate	Advantages
1.	Jyothi S. Nayak, Indiramma and Nagarathna [4]	Self -Principal Component Analysis (PCA) Based Method.	FG-NET	70%	Self-PCA based method shows improved recognition rate in comparison with PCA.
2.	Jyothi S. Nayak [3]	Novel Self-PCA Based Approach	FG-NET	95%	The recognition rate obtained is more promising and more accurate compared to other papers.
3.	Ravi Pal and Ajith kumar Gautam [13]	Pose Correction Using AAA Model	FG-NET	76.60%	This method overcomes the problem in generative methods as in that there is need of a training set of subjects with minimum variations in pose and illuminations.
4.	Amal Seralkhatem Osman Ali, Vijanth Sagayan, A Malik Saeed, H Ameen, A Aziz [12]	Local Binary Pattern (LBP) Texture Descriptor	FG-NET	95%	Improves the verification accuracy of the system to above 93% over a dataset comprising a wide range of age groups.
5.	Gayathri Mahalingam and Chandra Kambhamettu [2]	PCA Factorization And Simple Deterministic Algorithm	FG-NET	--	Effective representation of the spatial relationship between the feature points of an image can improve the performance of a face recognition system across age progression.
6.	Nana Rachmana Syambas and Untung Hari Purwanto [5]	Photoscape V3.5 Software, While The Verification Using Verilook 5.0/Mega Matcher Verilook 4.0 Algorithm Demo.	FG-NET	98%	The simulation results show the combination of image processing with contrast and sharpen increase the enrolment process by 17.14% and In verification process, the results of the combination increase the success rate of matching faces by 13.57%.
7.	Huiling Zhou, Kwok-Wai Wong, and Kin-Man Lam [18]	Canonical Correlation Analysis	FG-NET	The recognition rate is increased by 1.8% to 20%, depending on the age difference between the face images.	By comparing it to those existing face recognition methods on face images with age differences, this algorithm can improve the recognition rate significantly.
8.	A.Sindhuja, S.Devi Mahalakshmi, Dr.K.Vijayalakshmi [8]	Scale Invariant Feature Transform (SIFT) And Multi Scale Local Binary Pattern (MLBP)	FG-NET	MFDA gives high recognition rate with nearest neighbor method	PCA and random subspace is done to reduce the dimensionality and then whitening is performed to reduce the intra personal variations.
9.	Felix luefei-Xu, Khoa LUU, Marios Savvides, Tien D. Bui, and Ching Y. Suen [9]	Walsh-Hadamard Transform Encoded Local Binary Patterns	FG-NET	98%	novel subspace modeling method has gained significant improvement by building subspaces on WLBP featured image

Table 2. The Recognition Rate performance of different Age Invariant Face Recognition on various aging database

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S.No	Author	Method	Database	Recognition Rate	Advantages
1.	Zhifeng Li, Unsang Park, and Anil K. Jain [1]	Feature based method (SIFT and MLBP)	MORPH and FG-NET	FG-NET-47.5% and MORPH-83.9 0%	A fusion of discriminative and generative models further improves the face matching accuracy in the presence of aging.
2.	Tianyue Zheng, Weihong Deng, Jiani Hu [14]	Age estimation guided convolutional neural network (AE-CNN)	MORPH and CACD	98.13%	Face recognition rate is improved because of AE-CNN method
3.	Yandong Wen, Zhifeng Li , Yu Qiao [15]	Latent factor guided convolutional neural network	MORPH Album2, FGNET, and CACD-VS	MORPH-97.51% and FG-NET 98.5%	Reduces the variations caused by the aging process as much as possible.
4.	Dihong Gong, Zhifeng Li and Dacheng Tao [16]	Identity factor analysis (IFA)	MORPH, FG-NET and LFW	MORPH-92.6%, FG-NET-76.2% and Overall-94.56%	By maximizing the code entropy, face recognition performance can be improved by using a more compact and discriminative feature descriptor.
5.	Chi Nhan Duong , Kha Gia Quach, Khoa Luu , T. Hoang Ngan Le and Marios Savvides [17]	Temporal Non Volume Preserving (TVNP) transformation	FG-NET, MORPH, AGFW and CACD		Its advantages not only in capturing the non-linear age related variance in each stage but also producing a smooth synthesis in age progression across faces.
6.	Cui Meng, Jiwen Lu, and Yap-Peng Tan [19]	Hidden Factor Analysis (HFA)	MORPH and FG-NET	MORPH-91.14% and FG-NET-69%	Improves the rank-1 identification rate from 83.90% to 91.14%.
7.	Diana Sa, JiwenLu, Gang Wang, and Pierre Moulin [6]	Multiview discriminative learning (MDL) method	MORPH and FG-NET		Best recognition accuracy among all the compared methods.
8.	Djamel Bouchaffra [7]	Kernelized radial basis function technique	Georgia Tech, MORPH and FGNET	GeorgiaTech-83.6%,Morph-83.8% and FG-NET-48.6%	The benefit of expressing p(x) is invaluable since it allows the estimation of some parameters and the generation of other points in case where face images of the same individual are lacking.
9.	Junyong Si, Weiping Li [10]	PLS (Partial Least Square) model	FG-NET, MORPH	FG NET-74.7% and MORPH-89.7%	Robust to age-invariant face recognition with both large and small age gaps.
10.	Xiaonan Hou, Shouhong Ding, Lizhuang Ma [20]	PCA and LDA	CACD and MORPH	CACD-64% and MORPH-94.5%	Robust to intra-personal variance and discriminative to different subjects.
11.	Dihong Gong,Zhifeng Li and Dahua Lin[11]	Hidden Factor Analysis (HFA)	MORPH and FG-NET	MORPH-91.14% and FG-NET-69%	Improves the rank-1 identification rate from 83.90% to 91.14%.

III. DISCUSSION

The proposed paper comprehensively discussed a critical survey of existing literature on age invariant face recognition approaches. Table 1 provides the recognition rate performance of different age invariant face recognition approaches on FG-NET database. Table 2 provides the recognition rate performance of different age invariant face recognition approaches on all the available aging databases.

All the face recognition methods listed in Table 1 and Table 2 are evaluated their algorithm using FG-NET, Morph, Morph album 2, CACD, Georgia Tech and AGFW aging database. Different types of texture descriptors such as SIFT, LBP, MLBP, PCA, LDA, IFA and various modeling techniques are applied to accurately classify the face images in spite of their age variations. From both the tables, it is observed that the highest recognition rate provided for FGNET and Morph database are 97.51% and 98.5% respectively using Latent factor guided convolutional neural network. Merits and demerits of various age invariant face recognition methods are also listed in Table 1 and Table 2.

IV. CONCLUSION

The main objective of this work is to provide a brief survey about various researches and results achieved till now in age invariant face recognition. Well known published papers of last decade are presented in a summarized form so as to provide brief idea about different methodologies adopted up to now, which lays a good foundation for the reader about future scopes possible in this field.

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