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Comparative survey on age invariant face recognition and verification techniques

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ABSTRACT: *Face recognition has now become an important area of research in Computer vision and image analysis and is being worked upon extensively with newer techniques emerging out and claiming higher accuracy rate of recognition than before. Each technique comprises possible factors like posing, illumination, occlusion, expression variations etc. that may affect the recognition rate, but very few consider the variations caused on human face due to ageing. This paper surveys the prominent published literature of last eight years to analyze and summarize the work done so far on age invariant face recognition or verification system and evaluate them on various scales like computational speed, accuracy, performance consistency in intrinsic and extrinsic conditions. The motivation for this paper is to provide a review of current age invariant models available in literature and estimate the best one that fulfills all features and conditions.*

Keywords: *Age invariance, Computer vision, extrinsic conditions, Face recognition, and intrinsic conditions*

I. INTRODUCTION

Face recognition system refers to computer aided software which performs the job of identifying a person with his face. This is usually done with help of an already stored database of test images which are compared with the probe image to find a match. Due to its numerous real time applications, development of fast and efficient Face recognition systems has gained wide interest among researchers of Computer vision. The pioneer work of first semi-automated Face recognition system is credited to Woody Bledsoe, Helen Chan Wolf, and Charles Bisson who developed it for an unnamed artificial intelligence company in 1960's. After that, in another 3-4 decades many popular recognition algorithms had been developed which include Principal Component Analysis using Eigen faces (Kirby and Sirovich,1987), Fisher's Linear Discriminate Analysis (Peter N. Belhumeur, Joao P. Hespanha and David J. Kriegman, 1997), Elastic Bunch Graph Matching using the Fisher face algorithm (Laurenz Wiskott, Jean-Marc Fellous, Norbert Kruger and Christoph von der Malsburg, 1999), the Hidden Markov model (Samaria, Young ,1994) etc.

The conditions that affect the recognition rate of any face recognition system can be divided as intrinsic factors (facial hair, glasses, cosmetics, ethnicity and gender) or extrinsic factors (illumination, pose, scale and imaging parameters like resolution, focus, imaging, noise, etc.)[1]. There has been sufficient amount of research done to maximize efficiency regardless of these settings [2, 3, 4, 5, 6, 7, and 8]. Another parameter that has recently attracted attention is ageing factor. It is a demanding factor as human face undergoes a lot of changes as it ages and these changes are not general for all individuals. Change in skull size, facial texture, facial hair growth, gain or loss of fat across face, presence of glasses etc. can significantly affect an individual's face which poses a challenge for any face recognition system. It is seen that performances of most algorithms reduce significantly when there is a considerable difference of age between the test image and probe image. Therefore there is an increased interest in development of an age invariant face recognition system which is evidenced by the emergence of various new algorithms and models being developed. This survey aims in tracking and summarizing the growth of various such systems so as to get a glimpse of achievements made so far in this area and enable a clearer view of what lies ahead.

II. AGE INVARIANT FACE RECOGNITION TECHNIQUES

II.1 Lanitis, Taylor and Cootes [9], 2002

Lanitis et al proposed a model based face recognition in which the age progressive training set is projected onto a model space. The face model thus formed contained 50 model parameters and is a combination of shape and intensity model. The variation caused due to aging effect is isolated using an aging function (linear, quadratic or cubic) which operated on the model parameters to produce the actual age of the image. After the estimation of age, using appropriate ageing function, the model parameters are converted into new set of parameters corresponding to the target age. The test and training image parameters are obtained at target age which is the mean age of training set. Thus obtained parameters are used as feature vectors for recognition.

II.2 Wang, Shang, Su and Lin [10], 2006

Wang et al presented an age simulation model which transforms image to a target image for recognition. For age simulation, first using ASM model, shape features are extracted and is spanned to texture image by triangle based affine transformation. Shape Eigen face and texture Eigen face are acquired by applying PCA on shape and texture image, which are further combined to form facial feature vector. A polynomial aging function along with K-means classification of aging way is used for estimating age. This estimated age along with typical vector creating function was used to generate feature vector at target age. Finally the shape and texture vector were reconstructed in Eigen spaces and combined to produce facial image at the target age which was further used for recognition.

II.3 Ramanathan & Chellappa [10], 2006

Ramanathan et al proposed Bayesian age difference classifier that is built on probabilistic Eigen space framework. To remove irregular illumination effects, better illuminated half of the image was extracted using mean and optimal mean intensity curves, under the assumption of bilateral symmetry. These half faces thus obtained were given the name of Point Five faces. An age difference classifier was developed in which difference of given pair of Point Five faces were grouped as Intra personal or Extra personal image difference by computing its Posteriori probability using Bayes rule. Those pairs which came out to be Intra personal were further classified into four groups representing their age difference by selecting the maximum of their Posteriori probabilities.

II.4 Ling, Soatto, Ramanathan and Jacobs [11], 2007

Ramanathan et al proposed using SVM classifier and GOP descriptor for efficient face recognition across aging. For any two given images, it is first mapped onto feature space using feature extraction function and then classified into two categories as intra personal or extra personal using support vector machine. The feature extraction function used is gradient orientations at different scales which forms a pyramid hierarchal representation. At each scale, the image values of previous scale are convolved with Gaussian kernel with 0.5 as standard deviation. Thus obtained gradient vectors are normalized to form gradient orientation at each scale. Thus for a given pair of images, the feature vector formed is the concatenation of cosines of difference of gradient orientations at each scale and pixel position. This SVM+GOP approach were compared to several other techniques to find it as the best technique for face recognition which includes aging effect. Also an empirical study on aging process was performed which showed that after an age difference greater than 4, the recognition rate saturates.

II.5 Park, Tong and Jain [12], 2008

Park et al has proposed a 3D deformable model that can accompany any pose and lighting invariant 3D model for age invariance. For converting a 2D face into 3D, a face mesh having 81 feature point vertices is formed and PCA is applied on these shape vectors to form shape space. The 3D shape space is a matrix of M number of rows and N number of columns, where M is number of distinct ages and N is number of distinct subjects. Each element of the space is a vector representing 3D shape of the face. For a given probe shape at age x, a weighted sum of the shapes at that age can be generated. Using these weights, a new artificial face can be generated at target age y. In the same fashion, a texture vector and space is also created. The model is then tested on Face VACS software and a slight increase in recognition rate is identified.

II.6 Mahalingham and Kambhanmettu [13], 2010

Mahalingham et al proposed an aging model combined with graphical representation of faces for constructing a more efficient face recognition system. The facial image is constructed as a graph with feature points as vertices. Each vertex is labeled by its descriptor i.e. texture information. To extract feature points, LFA (Local Feature Analysis) is used which constructs n kernels, where n is the number of pixels in the image. To reduce this dimensionality of the representation, Fishers Linear Discriminant method is used to choose a subset of kernels which has higher fisher score. These kernels correspond to the feature points in the image. After that, a uniform LBP (Local Binary Pattern) operator is used to extract feature descriptor of each feature point. For testing the model, two-step process is used. First, a graph is constructed using feature points as vertices and corresponding descriptors and likelihood score is calculated with each training image. The ones with highest scores are chosen for the next step of matching. The graph of the probe image is matched with training images and recognition result is calculated.

II.7 Li and Drygajlo [14], 2010

Li et al proposed a multi classifier Q stack aging model that creates a Q stack classifier which is a framework of stacking classifications with quality measures. Here Age is considered as the quality measure. The multi classifier scheme incorporates Global PCA patterns and Local Ternary Patterns (LTP) for feature representations. During training phase, universal background model of four Gaussian mixtures (UBMGMM) is trained on the images using 32 eigenvectors. After the PCA features are extracted from the test image, log likelihood ratio (LLR) is calculated. For LTP training phase, average face templates are created for each individual and Euclidean distance is calculated between the template and test image LTP descriptor for testing. The Log Likelihood Ratio (LLR) scores of both classifiers, along with quality measure i.e. age are combined to form evidence vector. After normalizing, the vector is input to SVM based linear or RBF kernels for verification. The results showed an increased verification rate as compared to baseline or single stack classifier.

II.8 Hsieh, Pan and Hu [15], 2011

Pan et al proposed a facial aging synthesis method which comprised of ASM model to detect facial landmarks and proper alignment of them, Log Gabor wavelet to analyze the landmarks and finally synthesizing age using decomposition maps to construct the image at target age. ASM is used to detect location information of important facial features and to attain geometric invariance, the distance between inner corner of eyes are made horizontal and the distance between chin and nose is made vertical. These two halves of the face are thus combined and philtrum of test and training image is matched. To obtained skin topographies, Log-Gabor wavelet decomposition maps are convolved with the face image. The higher frequency portion of the target image is placed on higher frequency portion of test image and thus formed decomposition map yields the final target image. The proposed method got 100% accuracy in aligning eyes, nose, mouth and all three in test and training set. Age synthesis was achieved successfully.

II.9 luefei-Xu, Luu, Savvides1, Bui, and Suen [16], 2011

Suen et al proposed the method of using per ocular region of human face for adding age invariance factor to face recognition system, as per ocular regions undergo least amount of changes as the face ages. Walsh-Hadamard Transform Encoded Binary Pattern (WLBP) based feature extraction technique is used and Unsupervised Discriminant Projection (UDP) is used to build subspaces on WLBP image. It is a fusion of Walsh-Hadamard Transform and LBP, in which LBP is not applied directly to raw image pixels but after some transformations. Walsh masks are used as convolution filter for faster location of local image characteristics. Walsh function is used to extract samples at integer points to produce 2D basis images. After Walsh coefficients are obtained, LBP is applied on them to get the feature points of the image. UDP has the potential to minimize local and maximize non-local characteristics of the image concurrently by formulating scatter matrix for both. Normalized cosine distance measurement is taken on to compute similarity matrix between training and test image. The results showed better recognition rate as compared to using PCA or LPP as classifier.

II.10 Li, Park and Jain [17], 2011

Park et al proposed a discriminative model that has densely sampled location feature description scheme with Scale Invariant Feature Transform (SIFT) and Multi Scale Local Binary Pattern (MLBP) as descriptors and Multi Feature discriminant Analysis (MFDA) as classifier. For feature extraction, the image to first normalized and divided into set of overlapping patches and each patch is represented by 88 and 408 dimensional SIFT and MLBP feature vector. Since, the resulting dimensionality is very high, MFDA framework is proposed to reduce dimensions and resolve over fitting problem. The feature sets of training images are divided into slices of same feature. PCA is applied on each slice to construct 10 random PCA subspaces and calculate within class scatter matrix for each subspace. Then each subspace is whitened to remove intra personal variations. Five different between class scatter matrix is constructed using bagging technique and thus 5 LDA classifiers are constructed for each of 10 subspaces. Thus each slice has 50 different classifiers. In testing phase, slices are made for each test image and classification outputs are calculated for each slice. Using the min-max score normalization scheme, these outputs are normalized and score sum based fusion rule is used for the final decision.

II.11 Nayak and Indiramma [18], 2012

Indiramma et al proposed a self PCA based approach to attain an age invariant face recognition system. The per ocular region was cropped from all training images as it is considered the region which is least affected by aging and is unique to every individual. After cropping, an Eigen space was constructed for each image. The test image is matched by projecting onto Eigen space of each image and finding the minimum Euclidean distance between each. This method varies from conventional PCA in the fact that the Eigen space is not constructed for whole training set but for each individual.

Table-1 table showing various age invariant methods and their accuracy

Author	**Year**	**Approach**	**Database**	**Subjects**	**Images**	**Rank-1 recognition accuracy reported**
Lanitis et al	2002	Building Aging	Private	12	85	68.5%
Ramanathan et al	2006	Bayesian Age difference	Private	200	NA	-
Wang et al	2006	ASM + PCA	Private	NA	2000	63.0%
Ling et al	2007	SVM + GOP	Passport	-	200 intra- & 200 extra- personal pairs	97.5%
Park et al	2008, 2010	3D Aging model pattern based on PCA	FGNET	82	1002	37.4%
			MORPH	612	612	66.4%
			BROWNS	100	100	28.1%
Mahalingham et al	2010	GMM + GRAPH	FGNET	82	1002	80.0%
Li et al	2011	MFDA	FGNET	82	82	47.5%
			MORPH	10000	20000	83.9%
luefei-Xu et al	2011	WLBP+UDP	FGNET	82	1002	100.0%
Nayak et al	2012	Self PCA	FGNET	82	1002	95.0%
Mao et al	2012	LCEM	MORPH	-	200 intra- & 200 extra- personal pairs	80.0%
Sungatullina et al	2013	MDL	MORPH	5000	10000	65.2%
			FGNET	82	1002	91.8%

III. CONCLUSION

The paper focuses on providing a brief summary about various milestones achieved till now in production of a face recognition system that is invariant to aging of the face. Prominent 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. For MORPH database, the technique with the highest recorded accuracy is the one which uses WLBP as descriptor and UDP as classifier. And for FGNET, MLBP as descriptor and MFDA as classifier together gave the highest recorded rate of accuracy.

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