

# Machine Learning Based Age Invariant Facial Recognition System: A Review

**Manish and Sandeep Kumar**

M.Tech Scholar, Department of CSE

Assistant Professor, Department of CSE

CBS Group of Institutions, Village Fatehpuri, Jhajjar

mkyadav9897@gmail.com

**Abstract:** *Presently age invariance face recognition is an emerging research topic and has many potential applications. Face recognition under various intra-person variations such as expressions, pose and occlusion has been given adequate attention in the research filed. However, age invariance face recognition still faces many challenges due to age related biological transformations in presence of the other appearance variations. This paper surveys the prominent published literatures to analyze and summarize the work done so far on age invariant face recognition and to evaluate them on various scales like computational speed, accuracy, performances*

**Keywords:** Age invariance, computer vision, extrinsic conditions, intrinsic conditions, aging databases

## I. INTRODUCTION

Face recognition is an emerging research topic with numerous potential applications. It is a biometric approach that employs automated methods to verify the identity of a person based on the physiological characteristics. The aging of a person brings about a change in shape and texture of the face. It is a very complex process which depends on many factors like gene pattern, lifestyle, stress, environmental conditions etc. Automatic face recognition is an important yet challenging task due to aging variations, intra-user variations such as pose, illumination, expression and inter-user similarity [1].

Age invariant face recognition systems were not widely studied earlier because of the lack of suitable databases, but the recent advent of FGNET, MORPH and various other databases have made this area available for wide research field. N. Ramanathan and R. Chellappa [2] presented a Bayesian age-difference classifier that identifies the age separation between a pair of face images of an individual. This method was suitable to handle age progression in adult images, but not effective for handling age progression in face images of children. H Ling and S Soatto [3] 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.

N. R. Syambas and U H Purwanto [4] 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 [5] presented a graph-based image representation and an aging model constructed using GMM for each individual to model their age variations mainly in shape and texture. Here, a two stage approach for recognition is used 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. [6] used a self-PCA based technique to account for 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 [7] 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 [8] used 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, develop an algorithm, called multi-feature discriminant analysis (MFDA) to process these two local feature spaces in a unified framework. On facial aging, age progression and age estimation methods are surveyed in [9, 11, 12]. Whereas, a few face verification experiments across aging along with age progression and age estimation are reported in literatures. Initial works on the effect of aging on performance of AIFR has been addressed but it only uses FG-NET database [9-13]. 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. The rest of this paper is organized as follows. In Section 2, various aging databases are described. Section 3 deals with the age invariance face recognition methods. A comparative analysis of age invariant face recognition methods is tabulated in Section 4. Finally, the concluding remarks are given in Section 5.

## II. AGING DATABASES

Databases play very important and crucial role for testing of face recognition algorithms. Amongst many available databases only few of them address the aging problem. Due to lack of suitable and sufficient aging databases, age invariant issue has gained its attention very late. Now, many databases are available; a few of them are given below [15]:

FERET: This contains little age variations. It has total number of 14,126 images which has 1199 subjects and 365 duplicate set of images. It is hardly used for testing of AIFR algorithms.

FG-NET: It contains 1002 images of 82 different subjects. Its major limitations are less number of subjects available in database.

MORPH: It is a very large database. It has two sets, namely, album 1 and album 2. Album 1 contains 1690 face images of 625 subjects in the age group of 15-60 years. Album 2 contains 78,207 images of 20,569 different subjects.

Cross-age celebrity database (CACD): It contains 163,446 images of 2000 subjects. These images are collected from Google Image Search using celebrity name and year as keywords. Meta data details like name, age, identity, birth year is provided additionally.

Pinellas County Sheriff's Office Longitudinal Study (PCSO-LS): It contains 1.5 million images which are collected from the 18,007 criminals arrested by the Pinellas County Sheriff's Office (PCSO). It subjects have at least 5 face images collected over at least 5 years time of span. It does not contain images of subjects between age group of 0-15 years.

Wholslt (WIT): It contains 1109 images of 110 subjects which are collected from internet.

FACES: It contains 1026 images of 171 subjects with six expressions like neutral, sad, disgust, fear, angry and happy. All images are frontal with fixed illumination in the age group of 19-80.

ADIENCE: This database is collection of wild face images. It contains 26,580 images of 2284 subjects. This has variation such as appearance, noise, poses and lighting.

## III. AGE INVARIANCE FACE RECOGNITION METHODS

Facial aging process affects the appearance, shape and texture of the human face. Age related changes are dependent on intrinsic as well as extrinsic factors like, environment, lifestyle, exposure to sun, stress, diseases etc. Different aging pattern observed during starting years in children and adults. The bone structure does not change when person is fully grown. The aging in adult is characterized by the wrinkles, retrusion, sagging skin, eye slops etc. [14-15]. Shape change due to growth is presented by Thompson [16] while face anthropometric profile for describing human face certain characteristics is presented by Farank and Munro [17-18]. Age invariance face recognition (AIFR) has been broadly categorized into three categories: i) generative ii) discriminative and iii) Deep learning. The generative method is based on age progression methods to transform the probe image to the same age that of gallery image [9-10]. Discriminative methods handle recognition without age progression; instead, they rely on local feature descriptors. Discriminative



learning methods are further developed for feature matching in AIFR. Recently convolutional neural networks (CNN) have emerged as a powerful machine learning model. Deep learning based AIFR methods are treated as generative as well as discriminative methods [15].

### **1. 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 and performs normal mathematical operation on image. It has less output status in comparison to the discriminative model [5, 7]. Mostly, holistic methods use to generate face aging models and build aging functions to simulate or compensate for the aging process. An active appearance model (AAM) is used to study age estimation problems. In this technique, 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 algorithm, the feature points of an image and their descriptors are tried 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 posterior 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 [5, 7].

These face aging databases are usually collected from scanned images in different poses, illumination and expression and are insufficient to get the best fit results. In order to have an exact model to represent the aging process, one should to use a huge number of training images to 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 [5, 7].

### **2. Discriminative model**

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 [7].

#### **2.1 Densely sampled local feature description**

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 a  $s \times s$  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 [7].

## 2.2 Multi-feature discriminant analysis (MFDA)

The MFDA is used 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. To effectively handle these large numbers of features for enhanced performance, two problems should be overcome: 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.

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 selected 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 for the construction of the between-class scatter matrix. So, it is not completely random. The reason for adopting this strategy is the large numbers of inter-class sample pairs and not all the sample pairs contribute to the learning of discriminative model. Hence, it is viable 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 [7].

## III. 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 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 eigen face 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 eigen faces obtained [6].

## IV. DEEP LEARNING VS NEURAL NETWORKS

Neural networks are a set of algorithms, modeled loosely after the human brain, that are designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or clustering raw input. In deep learning, a convolutional neural network (CNN) is a class of deep, feed-forward artificial neural networks, most commonly applied to analyze visual imagery. The neural networks are used in many applications but the main objective of the neural network in the face recognition is the feasibility of training a system to capture the complex class of face patterns. In the neural network number of layers, numbers of nodes, learning rates, etc are tuned extensively. The neural networks



are non linear in the network so it is widely used technique for face recognition. So, the feature extraction step may be more efficient than the principal component analysis. More than 90% accuracy in the face recognition process was achieved in literatures. Normally, neural networks are also more computationally expensive than traditional algorithms. State of the art deep learning algorithms, which realize successful training of really deep neural network, can take several weeks to train completely from scratch. Most traditional machine learning algorithms take much less time to train, ranging from a few minutes to a few hours or days [19-20]. Multi-Layer Perceptron (MLP) with a feed forward learning algorithms was introduced for its simplicity and its capability in supervised pattern matching. It has been successfully applied to many pattern classification problems [21].

Research with deep learning concept is that it is the class of machine learning algorithm which has features like: i) It has many cascaded layers for feature extraction. The output of one layer serves as input of second layer and ii) Higher level features are derived from lower level features to form hierarchical representation. The layers used in the deep learning are the hidden layers of the artificial neural network. One more advantage of deep learning is that layers selects best features. Neural networks are trained using the gradient back-propagation method. The weight of a layer is updated as the derivative of previous layer [22, 28-29].

Instead of using hand-crafted features in machine learning's, deep-learning-based methods are nicely used in face recognition. Taigman et al. [22] present a deep model using the convolutional neural network (CNN) called deep face that achieves near human level performance in face verification. Yi Sun et al. [23] extracted deep feature representation for face recognition by using jointly face identification and verification to perform a supervised training of the CNN. A number of deep learning methods have been applied to handle face recognition problems [24-27]. Nowadays, CNNs are showing remarkable performance in the AIFR field. However, studies on CNNs are still limited and needs more attention of research.

## V. COMPARATIVE ANALAYSIS

This paper discusses a critical survey of existing literatures on age invariant face recognition methods. Table 1 provides the recognition rate performance of different age invariant face recognition approaches on FG-NET, MORPH, CACD and other databases. 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 the Table 1, it is observed that the highest recognition rate provided for FGNET and Morph database are using latent factor guided convolutional neural network. Our major focus in this survey is three categories presented for AIFR techniques to address the recognition across the different perspectives. Although, generative approaches are useful to certain extent, but their performance mainly degrades due inefficient aging models. Dependencies of facial aging on large intrinsic and extrinsic factors, along with incomplete databases are major limitations for making accurate aging models. CNN based generative models are not much explored and needs to be given more research attention. Deep learning approaches can capture the diverse aging patterns and have also shown improvements in the age estimation accuracy [15, 30-32].

Discriminative methods depend on age invariant facial features and discriminant learning techniques. The discriminative methods have potential to address the major AIFR problems. Large dimensionality is one of the limitations of the local feature descriptors in discriminative approaches. In manifold learning, local features are projected onto a low dimensional manifold but identifying a true age invariant manifold is a complex research problem. Deep learning AIFR methods are capable of learning a huge number of faces in presence of aging and other variations and offer high level of FR performance. These approaches require large sized databases for face representation and subsequent learning.

## V. CONCLUSION

The AIFR system faces challenges due to appearance variations within a subject and similarities between the subjects. We categorized the surveyed AIFR approaches in three categories: generative, discriminative and deep learning. Every approach takes the AIFR problem differently. Generative AIFR use aging models for age transformation while



discriminative approaches rely on age invariant features and learning schemes. Deep learning methods offer an integrated framework for face representation and classification. But complete training of deep learning networks which require large training data, using small databases like FG-NET) remains a challenge.

Performance of AIFR system shows different trends for different ethnic origins, males and females. Since facial aging depends on various factors besides aging, it is important to analyze the effect of intrinsic and extrinsic factors on the performance. Hence, for more accurate evaluation of AIFR algorithms, a facial aging database with correct demographic information and wide intra-person variations is need of the hour. A single database featuring a large and equal number of faces per person, across all the age groups is badly needed. Shortly, despite significant progress in AIFR, it is still far from expectations. CNN based methods are showing remarkable performance but study on CNN are still limited and needs more attention in AIFR research field.

### REFERENCES

- [1] A. Kumar, A. V. Srivastava and P. S. Yadav, Survey on age invariant facial recognition, Advances in Computer Science and Information Technology , vol. 2, no. 5; pp. 450-453, 2015.
- [2] N. Ramanathan and R. Chellappa, Face verification across age progression, IEEE transactions on image processing, vol. 15, no. 11, 2006.
- [3] H. Ling, S. Soatto, N. Ramanathan and DW. Jacobs, A study of face recognition as people age, IEEE International Conference on Computer Vision, pp. 1-8, 2007
- [4] N. R. Syambas and U. H. Purwant, Image processing and ace detection analysis on face verification based on the age stages, 7th IEEE, Int. Conf. on Telecommunication Systems, Services and Applications, 2012.
- [5] G. Mahalingam and C. Kambhamettu, Age invariant face recognition using graph Matching, Fourth IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS), 2010
- [6] Jyothi S. Nayak and Indiramma M, Efficient face recognition with compensation for aging variations, IEEE 4th Int. Conf. on Advanced Computing, pp. 1-5, 2012.
- [7] S. Jyothi Nayak, M Indiramma and N. Nagarathna, Modeling self-principal component analysis for age invariant face recognition, IEEE Int. Conf. on Computational Intelligence and Computing Research, 2012.
- [8] Z. Li, U. Park, A. K. Jain., A discriminative model for age invariant face recognition, IEEE transactions on information forensics and security, vol.6, no.3, September 2011.
- [9] A. Lanitis, A survey of the effects of aging on biometric identity verification, International Journal of Biometrics ,vol. 2, pp. 34–52, 2009.
- [10] A. Lanitis, CJ. Taylor and TF. Cootes, Toward automatic simulation of aging effects on face images, IEEE Trans Pattern Anal Mach Intell, vol. 24, pp. 442–455, 2002.
- [11] N. Ramanathan, R. Chellappa and S. Biswas, Computational methods for modeling facial aging: a survey. J Vis Lang Comput, vol. 20, pp. 131–144, 2009.
- [12] Y. Fu, G. Guo and TS. Huang, Age synthesis and estimation via faces: a survey, IEEE Trans Pattern Anal Mach Intell, vol. 32, pp. 1955–1976, 2010.
- [13] A. Lanitis, C. Draganova and C. Christodoulou, Comparing different classifiers for automatic age estimation, IEEE Trans Syst Man Cybern B Cybern, vol. 34, pp. 621–628, 2004.
- [14] K. Ricanek, A. Sethuram, EK. Patterson, AM. Albert and EJ. Boone, Craniofacial aging Wiley handbook of science and technology for homeland security, 2008.
- [15] M. M. Sawant and K. M. Bhurchandi, Age invariance face recognition: a survey on facial aging databases, techniques and effect of aging, Artificial Intelligence Review, Springer, pp. 1-28, 13 October 2018.
- [16] Thompson DW, On growth and form Cambridge, England, 1917.
- [17] L. Farkas, Anthropometry of the head and face. Raven Press, New York, p XIX, 1994.
- [18] L.G. Farkas, I.R. Munro, Anthropometric facial proportions in medicine. Charles C. Thomas, Springfield, 1987.



- [19] Ming-Hsuan Yang, D. J. Kriegman and N. Ahuja, Detecting Faces in Images: A Survey, IEEE Trans on Pattern Analysis and Machine Intelligence, vol. 24, no. 1, January 2002.
- [20] M. Kirby and L. Sirovich, Application of the Karhunen-Loeve procedure for the characterization of human faces. IEEE Trans. Patt. Anal. Mach. Intell., vol. 12, no. 1, pp. 103-108, 1990.
- [21] Li X. and Areibi S, A Hardware/Software code sign approach for face recognition, The 16th, International Conference on Microelectronics, Tunisia, 2004.
- [22] Y. Taigman, M. Yang, M. Ranzato and L. Wolf, Deepface: Closing the gap to human-level performance in face verification in CVPR, pp. 1701–1708, 2014.
- [23] Y. Sun, Y. Chen, X. Wang and X. Tang, Deep learning face representation by joint identification-verification in Advances in Neural Information Processing Systems, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds., pp. 1988–1996, 2014.
- [24] Z. Zhu, P. Luo, X. Wang and X. Tang, Deep learning identity preserving face space, in ICCV, pp. 113- 120, 2013.
- [25] Y. Zhang, M. Shao, E. K. Wong and Y. Fu, Random faces guided sparse many-to-one encoder for pose-invariant face recognition, in ICCV, pp. 2416–2423, 2013.
- [26] M. Kan, S. Shan, H. Chang, and X. Chen, Stacked progressive autoencoders (spae) for face recognition across poses, in CVPR, pp. 1883–1890, 2014.
- [27] H. Zhai, C. Liu, H. Dong, Y. Ji, Y. Guo and S. Gong, Face verification across aging based on deep convolutional networks and local binary patterns, in International Conference Intelligence Science and Big Data Engineering, pp. 341–350, 2015.
- [28] Y. Naik, Detailed survey of different face recognition approaches, International Journal of Computer Science and Mobile Computing, Vol.3, Issue.5, pp. 1306-1313, May- 2014.
- [29] D. Sinha, J. P. Pandey and B. Chauhan, A deep learning approach for age invariance face recognition, International Journal of Pure and applied Mathematics, vol. 117, no. 21, pp. 371-389, 2017.

