Aging Face Recognition Using Deep Learning

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Abstract— **Deep learning based approaches has gained very optimistic results in face recognition area. Face recognition is become very effective research topic and has a of a number of attainments. Also there are some researches for periocular recognition to overcome limitations of entire face recognition. The challenges of aging in periocular recognition has not gained attention after its achievements. Deep learning approaches are used to overcome many challenges of face recognition such as pose, expression, illumination and aging. Periocular images recognition under less restricted environments is the problem researchers faced in face recognition. But proposed approach has a new structure that can get efficient periocular recognition. This work focuses on the aging face recognition problems of entire face image based on a deep learning method, in particular, convolutional neural network. The proposed methodology gives a deep learning based approach for periocular recognition subject to aging. Using a CNN feature extraction and classification characteristic of deep learning gives an accurate and efficient recognition rate as compared to conventional method.**

Index Terms— **Deep Learning, Face Recognition, Convolutional Neural Network (CNN), Aging Face recognition**

I. INTRODUCTION

Face recognition is still very challenging and complex problem. This problem can be credited as large intra-personal variations and large inter personal similarity. Figure 1 shows intra personal variations of a subject consist of illumination, expression, pose and aging [1]. These variations are experienced in face recognition problems. Nowadays, aging variation is undergoing intense study in face recognition area as compared to other variations. Aging is very complex process which changes from person to person. Also, aging mainly depend on geographical location, lifestyle, eating habits, use of cosmetics, overall health of a person etc. of a person. An aging face recognition method is used in many applications, like passport verification, law of enforcement, missing children, surveillance etc. where facial images are included. Many researchers presented the approaches which focused on age estimation and age simulation facial aging problems.

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Figure 1: Example images showing intra-subject variations (e.g., pose, illumination, expression, and aging) for one of the subjects in the FG-NET database

Discriminative models based approaches presented for the aging problem to overwhelm the problems occurred in face recognition. Generally human faces grow in same manner as the age progresses, but each one has different features in face aging as they are from different ethnic and gender group. Therefore, it is insufficient to assume that similar faces age in similar ways for each and every individual. These limitations can overcome by using a very dense region of the face that is periocular region. This region gives discriminative information of face to extract local features which is different for every subject. The local features intrinsically give recognition rate as compared to general feature based approaches. Because of these properties local feature representations become powerful to aging, illumination, and expression variations. By the consideration the entire face has high complex structure which can changes by the time in the terms of color, structure and texture. Due to that it is demanding to models entire face for age invariance. Periocular region is very dense region of face which changes very little over the time because the mouth, chin, cheeks is vulnerable to changes and results loosened skin, while location and eyes shape remain unchanged.

Moreover, periocular area has the most complex and the densest biomedical features like eyebrow, eyelids, contour, eyeballs etc. on human face, which could all different in shape, size and color. But this is not efficient for the large size data in controlled and uncontrolled environment. Because, the traditional face recognition methods be composed of four steps: i) face detection, ii) face alignment, iii) feature extraction (or face descriptor) and iv) classification. Maybe the most important stage in face recognition is feature extraction. One more important issue in this application is about the changes in the images of the same person over aging i.e. intra personal variations and similarity in the images of other persons i.e. inter-subject similarities. This application basically consists of two categories, first is Aging Face Recognition (AFR) and second is Aging Face Verification (AFV). Though researchers proposed various methodologies as solution to this problem and improve recognition accuracy, there is still a scope to improve accuracy. The features extracted by CNN are more vigorous to complex variations amongst same subject images (intra personal) as compared to the conventional handcrafted features. The Deep Learning tasks recognition and classification in single structure by taking images directly, while conventional methods use the feature vectors instead of images. Deep learning determined the feature automatically which are important for Classification.

This paper focused on Aging Face Recognition problem by using Convolutional Neural Network, named as AFR-CNN. Deep learning using CNN has become very popular nowadays. The edge of it is feature extraction of face image and classification in a single structure. But there is no any logic or standard order to deciding the details of CNN Architecture. Researchers presented their methodologies using CNN, and it is focused only on their own architecture not on any specific reason behind using those details. These details incorporate the layers count in the network, sequence of these layers, dimensions of the filters applied, and number of neurons used etc. Hence, we also present our own methodology to design the CNN architecture for AFR. The remaining the paper followed by, Second section includes the related work done in this area. The next section gives complete details of the proposed methodology for aging face recognition. Finally, fourth section presents conclusion.

II. RELATED WORK

The previous work in aging face recognition area is followed by this section. Recently, researchers focused their work on face identification or recognition problem and face verification problem. This research is basically categorized in two types: Global and Local Approaches. Global approaches generate face models as generative models. Global Approaches need to develop synthetic images of the person at the required age and then perform matching of those images with given image. Local approaches generate face models as discriminative models. Local Approaches need their own way to extracting features and classification purpose so that two images of same person are matched. Summed to above approaches, models of conventional methods are hand designed. Now, deep neural network has gained considerable interest. And Convolutional Neural Network (CNN) is a deep neural network can learn the variations from the data without any prior knowledge. By applying a CNN approach, we can deal with to a large training data and uniformness exists in the data. We can get the result with a less time by using certain number of CPU cores and GPU.

A. Global Approaches

For Global approaches, usually to reduce the aging effect one face face image is transformed from one age to the required age which is known as age simulation models. Recently, two level learning hierarchical model based approach is presented in [2] with a feature descriptor called as LPS (Local Pattern Selection) for solving the problem of aging face recognition. Sethuram et al.[3], proposed Active Appearance Models, support vector machines (SVMs) and Monte-Carlo based face aging model that simulation gives high accuracy. Ramanathan and Chellappa [4] presented a face growing model for people bellow the age of 18 years old for face verification as age progresses. Lanitis et al. [5], presented a model for the growing face where training set is estimated on a model space for face recognition. The face model thus formed contained 50 model parameters and is a combination of shape and intensity model. Then the model parameters are converted to new sets of parameters to be consistent to target age after age estimation using suitable aging function. Park et al. [6] proposed a generic method that consists of a 3D aging model to improve the face recognition performance. They used pose correction step and separate modeling for shape and texture.

B. Local Approaches

For Local approaches, vigorous feature extraction methods and discriminative methods for learning are applied to face images collected at different ages subjects. Gong et al. [7] presented a feature descriptor which is MEFD (Maximum Entropy Feature Descriptor) to recognize aging face images. It is a discriminant feature descriptor. To refine recognition accuracy a new feature-matching framework is also proposed as IFA (Identity Factor Analysis). Ali et al. [8] focused on a combine shape and texture features for aging face recognition. They adopted phase congruency feature for shape and LBP variance for texture feature. Tandon et al. [9] attempted a novel approach using LBP of particular region as ROI for aging face recognition. Xiao et al. [10] presented a novel method for face recognition using a combination of texture and shape descriptors, called as Biview face recognition algorithm. For texture feature subspace learning methods are used and graph is constructed for shape topology for face images. Chi-square measure is used as a difference (dissimilarity) measure to calculate the distance between two histograms. Yadav et al. [11] presented a system to improve the results of face recognition across growing age by using bacteria foraging fusion algorithm. To reduce aging effects, this approach used combined global and local facial regions feature extracted by LBP and bacteria foraging fusion.

Li et al. [12] proposed a method where, SIFT (Scale-Invariant feature transform) and MLBP (Multi-scale Local Binary Patterns) are used for feature description and multiple LDA-based for classification to generate classification as a decision through fusion rule. Ling et al. [13] proposed a discriminative method for face verification over progression of age. In this approach, GO (Gradient Orientation) and GOP (Gradient Orientation Pyramid) is used for feature description and SVM (Support Vector Machine) for a classification which results images in two groups as intra subject and inter subject. Ramanathan & Chellappa [14], proposed Bayesian classifier for age difference that is built on probabilistic Eigen space framework. In which intra personal pairs are classified into groups that representing their age differences. Luefei-Xu, Luu, Savvides1, Bui, and Suen [15], proposed Aging face periocular recognition where WLBP (Walsh-Hadamard Transform Encoded Binary Pattern) used for feature extraction only on preprocessed periocular region and UDP (Unsupervised Discriminant Projection) is used on WLBP image to build subspaces. Periocular region is dense part of face, this WLBP feature remains constant for periocular region. Li, Park and Jain [16], proposed a method that used Scale Invariant Feature Transform (SIFT) and Multi

Scale Local Binary Pattern (MLBP) for feature extraction and Multi Feature discriminative Analysis (MFDA) for classification. D.Sungatullina [17] proposed aging face recognition method, multi-view discriminative learning (MDL) where, scale invariant feature transform (SIFT), local binary patterns (LBP) and gradient orientation pyramid (GOP) feature desrciptors are for each face image. Then, MDL project different types of local features into a subspace which results the intra-class variation of each feature is minimized, the interclass variation of each feature of the same person are maximized.

C. *Deep Learning Based Approaches*

Face recognition models based on deep network always gives better performance as compared to the conventional methods. Deep networks can work as the human brain's thinking process. As we know brain distributed memory and conception of objects in vast network of neurons. Which is consistent with the deep network. CNN have become a very popular technique for Computer Vision applications. Many researchers used CNN for face recognition applications.

Nowadays, some commercial and academic institutions designed distinct deep networks, such as FaceNet is designed by Google [18], Oxford research group designed VGGNet [19], DeepFace is architecture by Facebook [20] and DeepID is designed by CUHK group [21]. It firstly utilizes deep network to feature extraction of face and then performs classification. DeepFace applied an integrated deep neural network using for face alignment in preprocessing step. In the classification, DeepID uses Joint Bayesian classifier to make the classification more vigorous. FaceNet exploits very deep networks to perform face recognition. It uses nearly 8 million images of 2 million people and applies the triple loss strategy to train the network. DeepFace model applies a network trained by 4 million images. Here we need to point out that face recognition in DeepFace are a two-step process. In [22], a method is proposed using a fusion of 2-D face images and motion history image (MHI) for face recognition based on 7-layer deep learning neural network. In [23], authors presented the novel use of deep learning using CNN for automatic feature extraction for vigorous face recognition across time lapse. VGG is very deep 16 layer CNN architecture in their experiments is used. Li et al. [24], proposed a new deep CNN model for aging face verification with 7-layer CNN architecture. Parkhi et al. [25] presented a model for face recognition either from a only one image or from a series of faces traced from video. It was 11-layer architecture for face recognition. Hu et al. [26] proposed three CNN architectures and conducted large scale assessment of CNN-based face recognition model. These architectures are: small (CNN-S), medium (CNN-M) and large (CNN-L). They used LFW dataset for experimentation. Taigman et al. [20] proposed a 9-layer deep neural network for face verification problem where they used alignment step and representation step to apply a piecewise affine transformation. Yi et al. [27] developed an effective representation for both face identification and verification with deep learning named as DeepID2. Many researchers presented their work on AIFR using various methods as discussed above, but only few studies reported for Age Invariant Face Recognition specially using Convolutional Neural Network.

III. UNITS

When under unconstrained environment the whole face is unavailable or iris recognition is not possible periocular recognition is most useful. A periocular region is repellent of expression variations and aging as compared with an entire face. As the problems of aging in the full face images are hard to solve, we propose a methodology where this problem can be solved by periocular region recognition. The face recognition challenge subject to aging is addressed by this study. The proposed system is based on convolutional neural network used for vigorous feature extraction approach for periocular recognition.

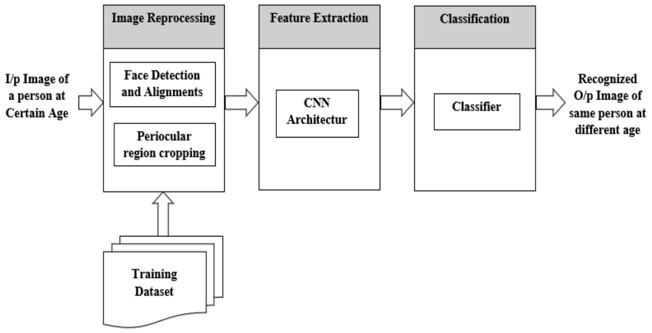

Figure 2: Basic Block Diagram for Proposed AFR-CNN

This section describes the proposed methodology for aging face recognition using convolutional neural network (AFR-CNN). This network is designed for the recognition of the person across ages. The overall process methodology contains the same steps that traditional methods have like image Preprocessing, Feature Extraction and Classification. The performance of the system improved by Image preprocessing steps. We will use two basic preprocessing steps, first is face detection and alignment and second is cropping of periocular region. Feature extraction is the process of capturing the desired feature descriptors using CNN rather than extracting it manually. In this model, we use VGGNet CNN architecture. Classification is required to recognize the person’s identity. The overall process for AFR-CNN is given in Figure 2.

In this work, for face alignment and detection we will use a deep flow of multi-task framework [29] which utilize the intrinsic correlation between detection and alignment to increase their performance. It holds a cascaded three stages convolutional networks architecture designed for face and landmark detection. The Proposed methodology (CCN-AFR) has 2 modules namely: the feature extractor and the classifier. The extractor module is categorized in three layers, convolutional layers, pooling layers and at last fully connected layers. And the module classification is constructed by fully connected layers. The fully connected layer which is output layer which is gives the recognition result is the last layer of the CNN architecture. Here, an input image is moved through several convolutional units and then a some fully connected layers. The fully connected layer with number of nodes represent the output as probabilistic prediction to the class labels. Here, publically available FGNET dataset will use. Due to robust features and large training samples, CNN gives efficient and high recognition rate. This methodology, Convolutional neural network based aging face recognition using periocular recognition

(CNN-AFR) is proposed to resolve the problem associated with existing work. We intended at solution of face recognition problem subject to aging in terms of accuracy and efficiency.

IV. Conclusion

The aging problem has remained unsolved for face recognition in aging. There are many researches for solving this problem for full face recognition which is quite difficult in uncontrolled environment. Aimed at resolving the existing problem of aging on full face image, the proposed system will present automated periocular recognition using CNN which can improve the efficiency of results and minimizes the complexity as compared to conventional methods. In particular, the proposed methodology can be a robust framework for the periocular aging recognition based on convolutional neural network.

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