Chapter 2

RELATED WORK

Objective
To bring brief description of existing related works on facial age progression.

Synthesized aged face image modeling can be roughly divided into three categories (a) prototype based approaches [9, 75], (b) anthropometry-model-based approaches [59] and (c) deep learning based approaches [41]. The prototype approach uses a non-parametric model for facial aging. These methods first divide the available faces into discrete age ranges and an average face is computed within each age range. This average face is treated as an age prototype for individual age groups. The difference between the prototypes is treated as the aging pattern to be transferred to each individual face in order to produce an aged face. However, the prototype approaches totally discard the personalized information and all the people share the same aging pattern.

The anthropometry-model-based simulate face aging by parametrically modeling shape and texture variations of facial muscles, cranium and skin. These approaches are generally very complex requiring a large number of face sequences of the same person with continuous ages.

Deep learning based methods are available for face verification, face recognition, age and gender identification and facial landmark detection. But for facial aging, very few works are currently available.

2.1 Prototype based Approaches

D. Burt and David Perrett [9] have proposed one of the earliest methods to get the aged face images, where they find the average of facial components from multiple face images and blend the input with that average. The output aged image of these average images depends on the age group of these averages of facial components of multiple face images.

In recent prototype-based method, S. Ira Kemelmacher et al. [37] proposed a technique which improves the result by replacing the input by the differences of average and texture under desired illumination between input and aged images.

A coupled dictionary learning (CDL) based models have been proposed by X. Shu et al. [63] and W. Wang et al. [78], which models learn the feature of various age grouped face images based on pre-designed dictionary of textures of various age groups. One limitation of this method is that output of this method has the look of ghost art-effects which does not seems like a normal face image.

C.-T. Hsieh *et.al.* [30] have proposed a simple face aging method based on face detection and "Log-Gabor Wavelet". Their method is also capable to get younger faces from older input face images using reverse-aging process. Using the information on skin surface topography for different age groups, they performed both age synthesis and reverse age synthesis to transform a test image into any age group of interest. Using edge detection technology they calculated wrinkle density values, and a wrinkle density index to get their results. The limitation of their method include that the system has issues including edge distortion and hair discoloration. When age changed, position of the landmark points remains unchanged. Whether some facial features may change their locations as facial muscles are weakened and cannot hold the tissues in their original places, but their technique cannot alter the shape or location of the facial features.

K. Luu et al. [45] proposed a method based on heritability factors of familial face images using "Active Appearance Models". Their approach is to find synthesized appearance of child's face towards adult ages using genetic features of facial parts of siblings and parents. Some limitations of their method is that, their proposal system does not work properly if the familial dataset is not found for any given input of a child image.

L.L. Kumari et al. [38] proposed a method to get older face images using morphing technique. They calculated the differences of mean distances to identify the facial features. Then they morphed identified facial features with a matched older image of the input from a given data set of images, and get the synthesised older face images. Limitation of their method is that it does not work with wrinkles, variations of face textures, changes of eye edge colour in the process of age progression.

A. Lanitis *et.al.* [56] and M. G. Rhodes [1] have proposed a relation on the progression of deformations of skin, which is based on statistical face model. Some other methods based on "Active Appearance Models" (AAM) can be found in [1, 19, 39, 45, 69–71], where AAM based methods basically explain the facial appearance effects on aging using learned age revolutions or conversion from younger to older face models.

2.2 Anthropometry-Model-Based Approaches

Anthropometry-model-based techniques are used to find the aged facial images with face models measured by estimated parameters of various facial parts. Some of the techniques developed under anthropometry-model-based can be found in [44], [21], [52, 53], [52], [4], [62] *etc.* A. Lin et al. [44] implemented simulation model for the growth of facial/head model from child to adult using anthropometric data from [21], which produce a statistical growth function. Also N. Ramanathan et al. [52, 53] projected craniofacial growth models to develop human aged facial model below 18 years. Ramanathan and Chellappa [52] have proposed a model using craniofacial growth function which calculated the growth-related shape variation functions of human faces during the period of childhood to adulthood. K. Ariyarathne [4], modelled a technique to simulate the facial changes with age progression of children who are below 18 years of age, where physically measured data of 2,325 Caucasian people have been collected, which find the differences of various facial parts.

C.-T. Shen *et.al.* [62] have proposed a technique named FAPP (Face Age Progression Prediction). In this method they have train a model to fit the growth curve of extracted facial parts like, eye, nose mouth *etc* of different age groups. Then based on the equation of growth curve, they find the aged facial images for the input of younger images.

2.3 Deep Learning Based Approaches

One deep learning based facial aging method have been proposed by G. Antipov et al. [3]. Some other deep learning based methods for face verification and recognition are available in [49, 67, 72].

Recently, some deep learning based methods of age and gender prediction are found in [41], [2], [20], [29], [46] *etc.* Using deep learning approach, G. Levi and T. Hassner [41] proposed a method that classifies age and gender of a given face image. To develop this method they have used "Deep-Convolutional Neural Networks" (CNN) for classification. However there method is not useful for finding older aged output face images. Al-Qatawneh *et.al.* [2] have described a method to get estimated ages based on transformation of facial shapes and "Cascade Correlation Neural Networks" (CCNN). They used features of face images and corresponding ages as two parameters in CCNN. Limitations of their method is that, it is only capable to find related ages for an input image but does not construct any synthesized older facial images. Some other age related and deep learning based methods are developed by A. Ekmekji et al. [20], S. Hosseini et al. [29], M. Duan et al. [18], W. MA et al. [46] *etc.*; again, all of these methods classify age or gender only and do not work on age progression.

Some recent work of facial landmark point detection techniques based on deep learning are proposed in [5, 23, 54, 66, 74, 86], which are briefly discussed in chapter 3 "Facial Feature Points (FFP) Localization".

2.4 Conclusion

Due to the subtleness of both facial structure and face aging mechanisms, anthropometry or physical model-based methods are often complex and computationally expensive. Few of the current face aging datasets can provide sufficient data to construct the model. These disadvantages make it difficult to obtain realistic results from physical modeling. The prototype approach does not require face sequences of the same person with continuous ages. This approach can be easily extended to PCA space and 3D face data. Deep learning-based methods also require large set of training data which is scarce. We are adopting the prototype based approach in the present work.