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AGE-INVARIANT FACE RECOGNITION: A LITERATURE REVIEW

Abstract. Facial aging, a new of the problem of face recognition, poses theoretical and practical challenges to the computer vision research community. There is growing interest in achieving age-invariant face recognition because of its broad applications. The main challenge lies in facial aging being quite a complicated process that involves both intrinsic and extrinsic factors. Facial aging also influences individual facial components (e.g., the mouth, eyes, and nose) in different ways. Numerous research efforts in the past decade have attempted to address the facial aging problem, using a variety of approaches. In this study, we review the research efforts and studies by the computer vision community that have addressed the facial aging problem and its influence on the face recognition task. We examine the facial aging process and its influence on changing facial features from a physiological perspective, as well as the challenges involved in modelling such changes to build an efficient face recognition system. Three-dimensional (3D) face modelling and computational modelling approaches and techniques are illustrated, along with the proposed systems related to them. Moreover, the most recently proposed systems, which have been built upon both generative and non-generative approaches, are examined in detail. The advantages and disadvantages of each proposed system are discussed as part of a comparison of these two approaches. The results achieved by the proposed age-invariant face recognition systems using these two different approaches are reported in term of recognition RANK-1 accuracy. We also provide a brief description of the publicly available face aging databases, including the FGNET, MORPH, and FERET databases. The aim of this study is to present the advances in the field of age-invariant face recognition in the last ten years to provide a clearer vision of the challenges that require further research and the possible solutions to these challenges.

Keywords: Facial aging; Computer vision; Physiological; 3D modelling; Generative; Non-generative; FGNET; MORPH; FERET.

1 Introduction

Automatic face recognition technology has attracted considerable attention because face recognition, in addition to having numerous practical applications, such as in bank card identification, access control, mug shot searching, security monitoring, and surveillance systems, is a fundamental human behaviour that is essential for effective communications and interactions among people [1].
The key challenges in designing a robust face recognition system consist of variations in lighting, expression, head pose, and aging [2]. A number of approaches have been proposed to accomplish lighting- and/or pose-invariant face recognition. Two of the best known among these approaches are novel appearance synthesis and discriminative feature extraction [3] [4]. Unlike other sources of variation (lighting, pose, expression, and occlusion), which can be controlled during face image acquisition, face aging is an inevitable natural process that occurs over the life span of a person. There has been increasing interest in developing age-invariant face recognition technologies to meet the needs of numerous applications in law enforcement and forensic investigation [2], including the following applications:

- **Homeland safety:** The accuracy of face-based verification systems that normally compare age-separated face images would benefit from facial aging models and from techniques that extract age-invariant signatures from faces. Additionally, in the absence of such systems, such authentication systems face the burdensome task of periodically updating large face databases with more recent face images.
- **Multimedia:** With growing needs to normalise the content explored by minors on the Internet, age-specific human–computer interaction systems have grown in significance in recent years. Consequently, methods that execute automatic age estimation are very significant to developing such applications. Moreover, the accuracy of age-based image retrieval and video retrieval systems would benefit from automatic age estimation systems.
- **Missing individuals:** Applications that can consistently predict a person's appearance over time have direct relevance to finding missing people.

In these applications, the age difference between probe and gallery face images from the same subject becomes one of the major challenges in face authentication. Lanitis et al. [5] conducted an experimental evaluation to quantify the effects of aging on face recognition. In their experiments, they used images from the FG-NET Aging Database [6] for training and testing face recognition systems. They concluded that, on average, the performance of face recognition system worsens by approximately 12% when examining faces with age distributions other than those in the training set and that the areas most affected by aging are also the most discriminatory regions. Consequently, it is of the utmost importance to address aging variation. The rest of this study is organised as follows. In the following section, we demonstrate the facial aging process with a detailed description. The rest of section 1 addresses the task of modelling the aging process and the modelling approaches, including 3D modelling. Section 2 describes various facial aging computational approaches and the challenges associated with building computational models for facial aging. Section 3 presents a comparison between generative and non-generative approaches, along with proposed studies for each of them. The publicly available face aging databases are described in section 4. Conclusions are presented in section 5.

1.1 The Facial Aging Process

The appearance of a human face is affected significantly by the aging process. Examples of aging effects on faces are illustrated in figure 1. Facial aging reflects the active, increasing effects of time on the skin, soft tissues, and profound structural components of the face and is a multifaceted synergy of skin textural changes and loss of facial size. Several facial manifestations of aging reflect the joint effects of gravity, progressive bone resorption, decreased tissue stretch, and reorganisation of subcutaneous fullness.

Environmental factors that are presumed to affect facial appearance include mental stress, diet, work routine, drug abuse, and disease [7]. The majority of the research into how aging affects the appearance of the human face has been focused on growth and development from infancy through early adulthood. Changes that occur over the remaining course of a lifespan have been found to be more difficult to quantify and characterise in detail. The study of common changes to the face is documented in anthropological literature that has yet to be employed to a great degree in computer approaches to modelling age progression of the face [8].

Fig. 1. Sample face images displaying aging variation. Each row shows images of the same individual at different ages. (These images were obtained from the FGNET database.)

A number of the studies undertaken have revealed general trends in the timing and patterns of changes in the face [9]. Research has provided information on when and what types of lines and wrinkles form and how skin elasticity and muscle tone decrease over time. Appearance is affected by diminishing muscle tone, diminishing collagen and elastin, and skin wrinkling and sagging. Soft tissue changes are clearly noticeable in the human face throughout the progression of aging, but skeletal changes or remodelling has also been documented. Research has produced proof of bone shape changes in the craniofacial region, including slight growth in head circumference, head length, width between cheekbones, and face height. Certain changes in the dent alveolar area and augmentation in anterior facial height have been found to lead to visual changes in the appearance of the lower portions of the face [10]. The rates at which these morphological changes occur vary. Soft tissue changes may not be readily obvious in the twenties and thirties, but changes occur more rapidly during the fifties and sixties [10]. Premature changes can include sagging of the eyelids, horizontal creases in the forehead, nasolabial lines, lateral orbital lines, circumoral striae, hollowing of the cheek at the inferior border of the zygomatic arch, decrease in upper lip size, and retrusion of the upper lip [6]. As aging continues, these changes become more visible, and by about fifty years, other changes begin, such as the appearance of multiple fine lines. The skin at this age is also thinner, rougher, and drier and exhibits loss of stretchiness. Further wrinkles appear on the face and neck, and discoloration of the skin may occur. Ordinary human variation occurs, of course, and factors such as gender, population of origin, body size, weight, and idiosyncratic behaviour may all affect facial appearance. In conjunction with craniofacial remodelling and soft tissue degeneration, other key factors affecting facial appearance with age include weight changes, sun exposure, ancestry, sex, health, disease, drug use, diet, sleep deprivation, biomechanical factors, gravity, and hyper-dynamic facial expressions [11]. Consideration of all of these age-related changes and their influences may be used to improve computer-based models of aging. Addressing aging variation is a challenging task because the aging process has the following unique characteristics:

- **Control:** Unlike other types of variation, the effects of aging cannot be controlled or inverted. This attribute of aging variation implies that (1) it is not possible to depend on the cooperation of a subject to eliminate aging variation in face image capture and (2) the collection of training data that are appropriate for use in studying the effects of aging requires long time intervals.

- **Diversity in Aging Variation:** Both the rate of aging and the nature of age-related effects vary among individuals. Diverse aging effects are normally encountered in subjects of different ethnic origins and different genders. External factors may also lead to diversity in the aging prototypes adopted by different individuals. Such factors include health conditions, lifestyles, psychological conditions, climate-related factors and purposeful attempts to interfere with the aging process through the use of anti-aging products [12] or cosmetic surgeries. Consequently, common aging patterns cannot be applied effectively to all subjects.

Moreover, facial aging effects are manifested in different forms in diverse age groups. Whilst aging effects are regularly manifested in the form of shape variations in human faces due to the cranium's growth from infancy to the teen years [13], they are more commonly observed in the form of textural variations, such as wrinkles and other skin artefacts, in adult faces.

1.2 Modelling facial aging

Typical human variation occurs naturally, and factors such as gender, population of origin, body size, weight, and idiosyncratic behaviour all may affect facial appearance [13]. In addition to craniofacial remodelling and soft tissue degeneration, other chief factors affecting appearance over time include weight changes, sun exposure, ancestry, sex, health, disease, drug use, diet, sleep deprivation, biomechanical factors, gravity, and hyper-dynamic facial expressions [14]. All of these factors and their influences on facial aging may be considered in improving computer-based models of aging. Among the challenges confronting the process of modelling facial aging are the following:

- There are large shape and texture variations that occur over a long period of time, i.e., approximately 20–50 years, such as hair whitening, muscles sagging, wrinkles appearing, etc. With the traditional Active Appearance Model (AAM) [15], it is hard to express all of these variations.
- The perceived face age usually depends on global non-facial factors, such as hair colour and style, the boldness of the forehead, etc., although these non-facial features are usually excluded from face aging modelling research efforts.
- It is very difficult to gather face images of the same person over a long time period, and age-related variations in such sequences of images, when available, are often mixed with other variations (e.g., illumination, expression, etc.).
- Large variations in apparent age exist within each biological face group, due to external factors, such as health, life style, etc.
- The literature on facial aging lacks quantitative measures for evaluating the results of aging.

1.3 3D Modelling of Facial Aging

The use of 3D face models and 3D range images has helped in achieving pose and expression invariance [16] [17]. 3D face matching is basically pose-invariant, and a deformable model can achieve robustness with respect to expression variation. However, even though range scanners and other 3D acquisition methods are becoming more capable, it may not be viable in the foreseeable future to substitute existing mug shot capture systems with expensive 3D systems and ask users to provide 3D images at both the enrolment and identification stages. Some of the approaches that have been proposed to overcome this limitation include applying a strategy involving matching two-dimensional (2D) images to 3D models, whereby the 2D probe images are compared to 2D renderings of the gallery 3D model for a variety

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of poses, lighting conditions, and expressions. Another option is to warp 2D probe images by 3D models fitted to those images and then compare the warped images to 2D gallery images. Modelling 3D human faces has been a challenging subject in computer graphics and computer vision research in past decades. Since the pioneering work of Parke [18] [19] [20], more than a few algorithms have been proposed for modelling the geometry of faces [21]. 2D-based methods do not accurately take into account the structure of a human face and therefore perform poorly on profile face images. In the work proposed by Lam et al. [22], face samples with out-of-plane rotation are warped into frontal faces based on a cylinder face model, but this warping requires extensive manual labelling work. Shape from shading [22] has been considered to extract 3D face geometry information and produce virtual samples by rotating the 3D face models generated. Nonetheless, this approach requires that the face images are accurately aligned pixel-wise, which is difficult to implement in practice and infeasible for practical applications. The two most popular works on 3D face modelling and analysis are the Morphable 3D face model introduced by Vetter et al. [23] and the artificial 3D shape model proposed by Zhang et al. [24]. Vetter et al. introduced a 3D reforming algorithm to recover the shape and texture parameters based on a face image in an arbitrary view, and Zhang et al. developed a system to construct a textured 3D face model from a video sequence. Recently, Hu and Yan et al. [25] proposed an automatic and much more rapid 2D-to-3D integrated face reconstruction technique to recover a 3D face model based on a frontal face. Nonetheless, there are limitations to all these approaches: 1) both Vetter and Zhang's approaches required manual initialisation, and their speed cannot meet the needs of practical face recognition systems; 2) Zhang's proposed system requires two images close to the frontal view and two conditioned sequences, including approximately 40 images, which is not feasible for practical applications; and 3) Hu and Yan's approach assumes permanent pose parameters, which restricts its extension to side-view images.

The major advantages of using 3D data are the following: although depth information does not rely on illumination, complete (180º) texture maps may comprise information from all potential views, resulting in a more robust approach against pose variations. 3D approaches can be divided into two categories: approaches that employ the same data format in the training and test phases [26] and approaches that take advantage of the 3D data during the training phase but then use 2D data in the recognition stage. It should be noted that the multimodal techniques introduced in [27] fall within the first category. Although such techniques can use depth only, texture only, or a combination of the two, they require that if frontal views are used during the training stage, then a depth or intensity frontal image must also be available in the recognition stage. Approaches in the first category have achieved even better results [28] than those in the second category; however, those in the first category have the major limitation that the acquisition conditions and elements of the test scenario must be well synchronised and controlled sequentially to obtain accurate 3D data. Consequently, approaches that use the same data format in both the training and test phases are unsuitable for surveillance applications or access control points where only one 2D texture image (from any view) from a single camera is obtainable.

The second group includes model-based approaches [29]. For example, in [29], a 3D face model for each subject in the database is constructed by integrating several 2.5D face scans from various viewpoints. The authors use the expression “2.5D scan” to convey the fact that the range and colour images obtained are only related to a part of the face and not its complete 180º representation (a complete 3D model). During the recognition stage, they fit the test 2.5D scan to each face model in the database using an iterative closest point (ICP) algorithm. Once they have coordinated the surface, they produce synthetic 2D texture images under the anticipated pose view for the 30 subjects in the database with the best surface matching. Lastly, they generate a 2D LDA face space with these synthetic training images by projecting the texture data of the input 2.5D scan. They consider texture and depth as two experts whose opinions they combine to identify the subject.

2 Facial Aging Computational Approaches

The use of computational models for understanding human face perception and recognition has a long and fascinating history that runs parallel to efforts in the computer vision literature to develop algorithms for computer-based face recognition systems. Up-to-date computational models have come into their own as commercial products. They are now built from composite plug-in components and solve a sequence of problems, including facial aging, from extracting a face from an image to running the information through pre-processing routines to delivering a final response. Developing computational models for human faces that accommodate diverse facial appearances, due to factors such as illumination variations, head pose variations, varying facial expressions, and occlusions, has long been a focus in the computer vision and psychophysics communities. Human faces express important information pertaining to individuals, such as their identity, gender, age group, and ethnicity, and facial expressions often assist in identifying the emotional states of individuals. Thus, perception studies propose that human faces are associated with high psychosocial significance and identify attributes such as facial attractiveness and facial aging as factors that influence interpersonal behaviour. From a face recognition viewpoint, various algorithms have been developed to perform still-image-based and video-based face recognition in the presence of illumination and head pose variations [30].

Typically, facial aging computational approaches address applications such as age estimation from facial images, appearance prediction across ages, etc. Age estimation is regularly performed by characterising the distances between key facial features and by studying the nature of facial wrinkles. Kwon et al. [31], Lanitis et al. [32], Gandhi [33], and Geng et al. [34] have proposed methods to estimate age from facial images. **Table 1** lists some of the previously proposed systems that have contributed to the field of age-invariant face recognition computational modelling, along with the approach adopted in each study [35].

Table 2. Proposed Systems for Age-Invariant Face Recognition Computational Modelling.

Reference	Approach
Haibin et al. [36]	Proposed a novel face

	descriptor to address facial aging effects.
Patterson et al. [37]	Studied the effects of morphological variations in faces on biometric systems.
Suo et al. [38]	Built a high-resolution grammatical face model to express aging effects.
Ramanathan, Chellappa [39]	Proposed an anthropometry-based facial augmentation model for young faces.
Ramanathan, Chellappa [40]	Characterised age-based appearance variations by means of subspace methods.
Gandhi [41]	Used an image-based surface detail transfer approach to imitate wrinkles.
Lanitis et al. [42]	Characterised facial aging effects using regression functions.
Tiddeman et al. [43]	Employed wavelets to model wrinkles on age-based face composites.
Burt, Perrett [44]	Characterised differences between age-based face composites.

2.1 Computational Modelling Challenges

Human proficiency with faces is typically described by the fact that humans have the ability to remember hundreds if not thousands of faces as “individuals”. This suggests an aptitude to extract and encode the information that makes a face unique. The computational challenges involved in this problem are of the following three types.

- First type of computational modelling challenges

The human vision system has, as input for the task of face recognition, two-dimensional projections of the three-dimensional environment—one image on each retina. The neural code for faces, and in fact, for the rest of the visible world, must either reconstruct the lost third dimension [45] or do without it [46]. Both strategies, by characterisation, force the vision system to depend on an error-prone or at least limited estimate of the real world. The dissociable information at the heart of this problem can be illustrated using data from a laser scan of a face, which separates the three-dimensional shape from the reflectance and pigmentation of the face. Any exclusive combination of shape and reflectance information, (e.g., from an individual face) can create a nearly boundless diversity of two-dimensional retinal images, depending on the illumination environment and the relative position of the viewer with respect to the head. This countless number of images must somehow be mapped to a single set of physical realities about the construction and reflectance properties of a face.

- Second type of computational modelling challenges

Despite the strategy that the neural system has evolved to handle its inadequate quality sample of the world, it must eventually encode and quantify the complex information in faces that is needed to survive—the distinctiveness of individual faces, the properties that identify age, sex and race, and the social and emotional communication information that faces express. Consequently, a single set of physical realities about the structure and reflectance attributes of a face must be adequate for the face processing tasks we do. Assuming that the visual system is able to compute a rationally valid set of measurements of faces, the problem of finding task-relevant information remains. Quantifying the composite variations in the three-dimensional shape and reflectance of a human face is by no means an insignificant task.

- Third type of computational modelling challenges

The unique information that specifies face identity is not present in absolute terms but rather is dependent on a reference population of relevant faces. A nose of a definite type has diagnostic value for identifying a person only to the degree that is unusual within the context of a population of faces. A neural code for faces will be most proficient if it references the amount and type of variability in a relevant population of human faces. Some element of this population referencing is required to account for several phenomena in human face recognition, including the recognition of other-race faces. In the context of other-race face recognition, the proper prototype or reference face is different, and our limited experience with other-race face populations may limit the quality of the representation we can create. These computational challenges relate to understanding human face representations from a neural and psychological perspective and are at the heart of the dynamic dialogue that has taken place between psychologists and computer vision researchers over the past two decades [47].

2.2 General Review of Age-Invariant Face Recognition Approaches

In the field of computer vision, the majority of aging approaches are example-based [30] and can be classified into three types [48]. 1) The prototype method [44] [49] computes the average face image of each age set as a prototype and defines the differences between prototypes as aging transformation. Wang et al. [50] applied this prototype approach in PCA space as an alternative to applying it to images directly, and Park et al. [51] applied it to 3D face data. The prototype technique is able to extract average patterns, but several details (e.g., wrinkles, pigments, etc.) critical for age perceptions are neglected. Other research has studied texture transfers from a specific senior face to young ones [52] [53]. 2) The function-based method describes relationships between a face image and its age label with a plain function, such as a quadratic function [54], support vector deterioration [55], a kernel smoothing technique [56], or an implied function [57]. Jiang and Wang [58] built a mapping function to connect young faces and their appearances at later ages. All of those functions need substantial real aging sequences to learn the function parameters. 3) Distance-based techniques [59] maintain aging simulation as an optimisation problem. They synthesise concurrently a face close to the images of projected age in age space and close to the input individual in the identity space. The algorithm in [59] employs a global AAM model and straightforward similarity metrics, but the simulation results are not realistic enough. Additional related work has been performed in age estimation, selecting discriminative features to estimate face age. The principal studies on age estimation [32] divided human faces roughly into groups based on facial landmarks and wrinkles. The latest approaches have considered the constant and temporal properties of face age and have formulated age estimation as a regression problem. Researchers have explored diverse features, including AAM coefficients [33], image intensities [60][61][62], and features that are designed heuristically [63] and have adopted various regression methods, such as quadratic functions [33], piecewise linear regression [33] [63], multi-preceptor projection [60] [33][63], etc. Taking a somewhat different approach, Geng et al. [64] defined an aging sequence as an aging pattern and estimated age by projecting a face instance onto the proper position of the proper pattern.

3 Generative Versus Non-Generative Approaches

Existing face recognition methods can be classified into two categories: generative and non-generative.

- **Generative methods**

  Generative methods apply simulation of the aging process as a first step, using a mathematical model. Subsequently, a recognition algorithm such as PCA or SVM is applied for matching faces between test images and gallery images.
- **Non-generative methods**

  Such methods tend to derive age-invariant features from the subjects' faces.

3.1 Work Using the Generative Approach

Lanitis et al. [42] proposed statistical models to perform face aging simulation. They used training images to study the relationship between coded face representations and the genuine ages of subjects. This relationship was then employed to estimate the age of a subject and restructure the face at any age, and for this purpose, they constructed an aging function based on a parametric model for human faces. To explain the effects of aging on facial appearance, they used PCA-based transformation models. The model they developed combines shape and intensity information to characterise the face images. Furthermore, their statistical models were used for other applications, including simulating aging effects and face recognition across age variations. The system was tested on a private database containing face images of subjects less than 30 years of age. In other work [10], they introduced four different types of aging functions, including the global aging function, wherein changes in aging appearance are assumed to be similar for all individuals; the appearance-specific aging function (ASA), wherein each individual has an aging function in the training set; the weighted appearance aging function (WAA), wherein the individual aging functions are combined with specific weighted parameters; and the weighted person-specific aging function (WSA), wherein the lifestyle profile of each individual is integrated with facial appearance into a weighted aging function. Because the system was trained using a comparatively small number of images, it learned to simulate age effects only in ways exhibited in the narrow training set. Consequently, the system will fail when the subject appears in a novel image representing a different aging pattern than the aging patterns of the subjects in the database. Moreover, they used local aging models, although the process of aging can be different for different age groups. Thus, there is a need for more specific age models.

Patterson et al. [54] proposed the use of explicit aging functions, mainly quadratic functions, to describe the relationships between a face image and its age label.

Ramanathan et al. [40] concentrated on infancy growth modelling, in which the facial transformation is very different in the childhood years than in the adult years. Their goals were to construct a model based on craniofacial growth (the augmentation of skull and face) and to model the facial landmarks that are most commonly known in anthropometric studies. In their modelling approach, the age-based anthropometric constraints on facial proportions are translated into linear and non-linear constraints on facial growth parameters. The problem then reduces to methods for computing the optimal growth parameters. The proposed approach lacks a textural model, and textural variations with age are not taken in consideration. Thus, facial hair, and other commonly experienced textural variations in teenagers are not considered. Moreover, the approach does not account for changes in the quantity of fat tissue in the face. The model preserves "baby fat", and therefore, the age transformation results obtained for toddlers were poor. However, the system has a number of advantages:

- Because the facial growth parameters computed at facial landmarks are the same across individuals, the facial growth parameters computed over the whole face region are adapted to each individual in a different way and therefore differs for each individual.
- The model accommodates gender-based differences in facial growth because it was developed using anthropometric data pertaining to men and women independently.
- The craniofacial growth model can be modified to characterise the facial growth of people of different ethnicities using anthropometric data pertaining to people of those ethnicities.

Chellapa et al. [33] studied the aging process in adulthood and proposed an aging model consisting of two stages: a muscle-based geometric transformation model that captures the delicate changes that occur in adulthood and an image-gradient-based texture transformation function that characterises facial wrinkles and other skin artefacts often observed at different ages.

Park et al. [65][66] designed an aging simulation technique to gain insight into the aging patterns of shape and texture based on PCA coefficients. A 3D morphable model is employed to model the aging variations from a set of 2D face images. The prototype technique is applied to the 3D face data. While the prototype technique is able to extract average patterns, many details crucial for age perception, such as wrinkles and pigments, are neglected. A classic approach for cross-age face recognition is to simulate the aging process for each individual and render new face images at different ages for matching. Park et al. fitted their 3D morphable model to a set of face images by fitting an active appearance model (AAM) and extracting a 3D model from the AAM. Aging is performed by calculating a set of weights between an input face and exemplar faces in the same age group. These weights are then used to build an aged face as the weighted sum of the resulting faces at the intended age.

Ramanthan et al. [33] developed a shape transformation model to capture the delicate deformations of facial features that are exaggerated by aging. Their model implicitly accommodates the physical properties and geometric orientations of human facial muscles. Subsequently, they developed an image-gradient-based texture transformation function that characterises facial wrinkles and other skin artefacts often experienced at different ages. The proposed facial aging model does not account for facial hair and therefore cannot address hair loss. Ramanthan et al. claimed that their model has the following advantages over other proposed aging models:

- Facial growth statistics: Facial measurements extracted for diverse facial features over time offer significant evidence of facial growth.
- The facial measurements were extracted mainly from Caucasian men and women. Thus, the model can accommodate gender-based and ethnicity-based facial growth patterns.
- For each of the instances, they calculated facial growth parameters such as weight loss or gain and retention independently and thus account for these factors effectively.
- The rates at which facial wrinkles are manifested on individuals' faces at different ages are frequently subjective. The proposed texture transformation model can be used to predict the different wrinkle patterns that could have been observed on an individual's face.

Ling et al. [67] employed the gradient orientation pyramid (GOP) for feature representation, combined with a support vector machine (SVM), to verifying faces at different ages. They were able to surpass the performance of the COTs FRs system by performing discriminative learning of face images with time lapse. They stated that it is generally accepted that face recognition performance suffers greatly as the time between acquisitions of images increases. One of the advantages of their proposed SVM+GOP method is that being a discriminative method it is able to confront the face identification problem directly. This way, the system not only avoids the potential instability caused by age estimation and simulation but also demands less prior information regarding the photos under comparison. In addition, GOP is known to be insensitive to illumination changes [68]. Accordingly, no normalisation of the input images is needed. Moreover, the pyramid method provides a natural way to perform face comparison at different scales. However, the experiments show that the pyramid method performs poorly in analysing the faces of small children from 0 to 8 years in age.

Mahalingam et al. [69] constructed a probabilistic aging model for individuals using a Gaussian mixture model (GMM) that incorporates both texture and shape information. They proposed a simple graph-structuring algorithm that uses the feature points of an image as vertices and their consequent feature descriptors as labels. Matching is performed in two stages. In the first stage, a maximum posteriors solution is computed using the aging model of the individuals to efficiently reduce the search space and identify candidate individuals for the second stage. During the second stage, a simple deterministic graph-matching algorithm exploits the spatial similarity between the graphs. The system was tested using the FGNET face aging dataset. The system performs well when tested on individuals ranging in age from 18 to 69 years, but for individual less than 18 years old, the system's cumulative accuracy degrades, which mean that the system cannot account effectively for aging variations in people who have not reached adulthood.

Li et al. [70] introduced an advanced algorithm for face recognition that is intended to be insensitive to age variations. This algorithm uses Multi-Feature Discriminant Analysis (MFDA), including a Scale-Invariant Feature Transform (SIFT) and Multi-scale Local Binary Patterns (MLBP), to encode the local features. Li et al. proposed both discriminative and generative aging models for age-invariant face recognition. The generative model is used to learn the parametric aging model in the 3D domain to generate synthetic images and minimise the age gap between probe and gallery images. Their system was evaluated in a set of face identification experiments, and it was found to outperform a leading commercial face recognition engine on the MORPH dataset.

Wu et al. [71] proposed a comparative craniofacial growth model based on craniofacial anthropometry. Their method employs a set of linear equations for the relative growth parameters that can be easily applied to facial image verification with aging. The researchers integrated the relative growth model with a Gaussian manifold and an SVM classifier. They were able to demonstrate how knowing the age could improve shape-based face recognition algorithms. Their system achieved performance comparable to that of the state-of-art texture-based method on the FGNET-adult dataset. The method performs better on the FGNET-adult dataset than the FGNET-children dataset, which is consistent with the fact that children's faces changes swiftly, while the facial shapes of adults are relatively stable.

Table 2 summarises some of the previous research in age-invariant face recognition based on the generative approach. In this table, we can see details of the method adopted in each study, the dataset used for testing or validating the proposed system, the number of subjects in the database used in the experiments, the number of test images considered for each subject, and the recognition accuracy reported for each proposed system, expressed as a percentage. In the last two columns of the table, the main advantages and disadvantages of each proposed system are summarised to provide a clear basis for analysing and comparing these systems.

Table2. Age-invariant face recognition—proposed systems based on the generative approach.

Reference	Method	Dataset	(No of images, no of subjects)	Result (%)	Advantages of the system	Disadvantages of the system
Lanitis et al. (2002) [42]	Build an aging function in terms of PCA coefficients of shape and texture.	Private database	500 images, 60 subjects	71	-The model combines shape and intensity information to represent face images. -The proposed system accounts for age progression, age estimation, and face recognition across age. -The model combines the advantages of learned aging functions with the capability	-Generalisation due to the small number of training images. -The use of a local aging model rather than a specific one.

					to employ person-specific age transforms.	
Ramanathan et al. [40]	Shape growth modelling up to age 18	Private database	233 images,109 subjects	58	-The facial growth parameters computed over the entire face region are adapted to each individual differently and hence	-Facial hair and other commonly observed textural variations in teenagers are not considered.
		FGNET	Not specified		are different for different individuals. -The model accounts for gender-based differences in facial growth. -The craniofacial growth model can be adapted to characterise the facial growth of people of different origins.	-The model retains “baby fat”, and thus the age transformation results for toddlers were poor.
Patterson et al. [54]	Build an aging function in terms of PCA coefficients of shape and texture	MORPH	9 subjects	33	-The results showed improvement of recognition accuracy in a basic PCA-based face recogniser using the proposed model. - The results are promising for modelling adult craniofacial aging.	The research considered a relatively small sample from a test dataset, and thus aging effects were not demonstrate in detail.
Park et al. [65]	Automatic simulation of the aging model using 3D Morphable model.	FGNET	1,002 images, 82 subjects	53.1	- The extension of shape modelling from 2D to 3D domain provides further capability of compensating for pose and lighting variations. - The proposed age modelling technique is capable of modelling the growth pattern as well as the adult aging.	The proposed aging model causes failure of matching after the aging simulation in multiple cases, which shows there is a need for improvement of the aging modelling technique.
Ramanathan et al. [33]	Shape and texture transformation models	Passport database and FGNET	520 images, 260 subjects	51	-Facial measurements extracted for diverse facial features across ages offer significant evidence of facial growth. - The model can account for gender-based and ethnicity-based facial growth patterns. -The model accounts for weight loss, gain, and retention. - The proposed texture transformation model can be used to predict the different wrinkle patterns that could have been observed on the individual.	The proposed facial aging model cannot account for facial hair and hence cannot address hair loss.

Mahalingam et al. [69]	Build a probabilistic aging model for each subject using GMM	FGNET	1,002 images, 82 subjects	69–80	- The combination of an aging model and graphical representation performs well in age-invariant face recognition. - The effective representation of the spatial relationship between the feature points of an image can improve the performance of a face recognition system with consideration of age progression. - The recognition performance is enhanced with the use of the two-stage matching process.	The system cannot account effectively for aging variations in infants.
Park et al. [66]	3D aging modelling	FGNET	82 images, 82 subjects	37.4	-Performs a pose correction stage and models the aging pattern more realistically in the 3D domain. -Separate modelling of shape and texture changes.	With the prototype technique used, many details crucial for age perception, such as wrinkles and pigments, are neglected.
		MORPH	612 images, 612 subjects	66.4		
		BROWN	100 images, 100 subjects	28.1		
Ling et al. [67]	Gradient-orientation pyramid combined with support vector machine (SVM)	Real passport photos dataset	1,824 image pairs, 1,824 subjects.	89.2	-The proposed system requires less prior information about photos under comparison. - GOP is insensitive to illumination changes consequently no normalisation is needed on the input images. - The pyramid technique provides a natural way to perform face comparison at different scales.	The method experiences difficulties with small children with ages from 0 to 8, where the method work poorly.
		FGNET	1,002 images, 82 subjects	75.9		
Li et al. [70]	Multi- feature discriminant analysis (MFDA)	FGNET	1,002 images, 82 subjects	47.5	The proposed discriminative model outperforms the FaceVACS by an obvious margin.	The proposed discriminative model is sensitive to pose variations.
		Extended MORPH	20,000, 10,000 subjects	83.9		
Wu et al.[71]	Craniofacial growth model	FGNET	1,002 images, 82 subjects	77	The proposed method achieves performance comparable to that of the state-of-art texture-based method on the FGNET dataset.	The proposed method is less reliable on the children set.

3.2 Work Using the Non-Generative Approach

Ramanthan et al. [41] proposed a Bayesian age difference classifier built on a probabilistic eigen-space framework to perform face verification across age progression. Instead of using a whole face, their model uses only a half face (called a five-point face) to address the non-uniform illumination problem. Then, eigen-space techniques and a Bayesian model are combined to capture intra-personal and extra-personal image differences. Their experiments were conducted using a database of pairs of face images that were collected from the passports of 465 individuals. The method is effective in addressing age progression in human faces that has direct relevance to passport image renewal applications. The verification results for facial images obtained as many as nine years attain have error rate of 8.5%. The method does not account for shape variations in faces; thus it may not be effective in accounting for age progression in the facial images of children.

Singh et al. [72] proposed an age transformation algorithm that registers the gallery and probe face images in a polar coordinate domain and minimises the variations in facial features associated with aging. They apply a Gabor feature-based face recognition algorithm on the transformed images. Their system requires further improvements to increase its accuracy for the 1–18 age group. Their results yielded better performance for the 19–40 age group.

Ling et al. [37] proposed the use of a face operator based on image gradient orientations extracted from multiple resolutions. They obtained parameters for an SVM that is used as a classifier for face verification across age. Figure 1 shows the computation of a GOP from a sample input image. They studied how age variations affect face recognition performance in a real passport photo verification task. The authors proposed a non-generative technique in which they define a face operator, derived on the basis of the image gradient orientations resulting from multiple resolutions, and then use support vector machines to perform face verification across age progression. Their experimental work showed that the complexity of the face recognition task saturates when the age gap between the probe and gallery images is greater than four years and remains so for age gaps up to ten years.

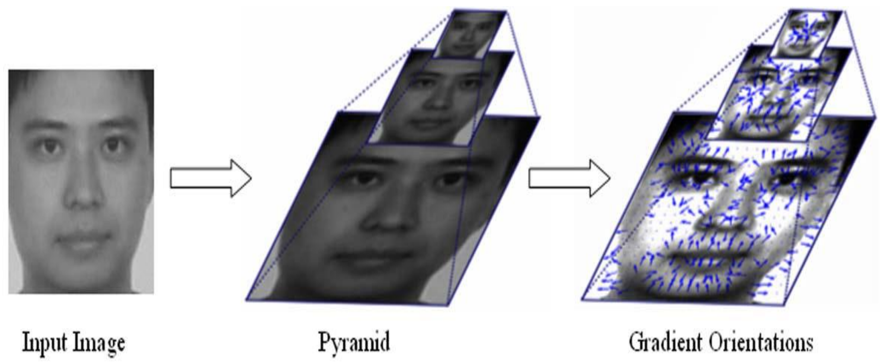

Fig. 2. Computation of a GOP from a sample input image [37]

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The method proposed by Biswas et al. [73] makes use of location drift of facial features with age. The key to their method is to search for coherencies in facial feature drifts with age. They stated that the coherency of some chosen facial features is greater in two different images of the same person at different ages. In their research, only the most frontal fiducially facial features are selected because the features on the outer boundaries of the face have a propensity to change rapidly with head pose variations and facial expressions. The proposed method is quite instinctive and simple when the coherency is defined as follows:

$$\bigcup ij = \frac{|c_{i-}c_j|}{a_{ij}} \quad \textbf{(1)}$$

Where $|c_{i-}c_j|$ the magnitude of the vector difference between the two features is drifts a_i and a_j and a_{ij} is the distance between the corresponding feature locations. The combined potential energy of the drift map, characterised by K feature drifts, is given by the following expression:

$$B = \sum_{i=1}^{k} \sum_{j=i+1}^{k} \cup ij \quad \textbf{(2)}$$

The smaller the potential energy B is, the more likely it is that the images belong to the same subject.

Textural variations with aging, which may be useful for matching age-separated images of adults, are not considered in this method.

Drygajlo et al. [74] adopted a Q-stack classifier, which is a structure for a stacking classification using quality measures to model the changes of the scores of the baseline classifiers and dynamically adapting the thresholds in the verification domain. The novelty of this approach is that it can automatically keep track of the tendencies of the facial changes of a particular individual over time. The researchers used YouTube videos of people who typically displayed their face every day for three years. The time span is greater than that of the other datasets, but the number of subjects is very small, and no ground truth is available (automatic image extraction can be invalid; nothing ensures that the pictures are presented in chronological order). Their proposed method minimises the error rates at levels below those of the baseline classifier created at the time of enrolment. This method assumes that multiple sample images are available for use in building the Q-stack classifier for each subject. The authors have stated that the permanence of biometric features for face verification remains a largely open research problem.

Li et al. [70] explored the difficulty that arises when there is only one test image per subject available. They proposed the use of an aging threshold mechanism to decrease the influence of aging on baseline classifiers through a score–age stacking technique that finds the global decision boundary that can change with age progression. This mechanism permits improved long-term class separation by introducing a parameterised decision boundary in the score–age space, using a biometric template created by a single reference image. They adopted the concept of classifier stacking and an age-dependent decision boundary to develop their system. Their results show that the tendencies of impostor scores are different from those of genuine subjects.

Meng et al. [75] proposed a method that uses three feature extraction methods: local binary patterns (LBP), Gabor wavelets, and a gradient orientation pyramid (GOP). PCA is then applied to reduce the dimensions of the extracted features. The researchers presented a comparison of the PCA, GOP, and Gabor wavelet methods, followed by a comparison of PCA and local binary patterns (LBP). Their experimental results for the MORPH database show that the Gabor wavelets feature with five scales and eight orientations is the best of the three feature representation methods considered for age-invariant face recognition, followed by GOP.

Narsaria et al. [76] adopted a triangular approach for face verification and age range estimation. Their system is based on extracting certain facial features (eye brows, eyes, and mouth) and coordinating the midpoints of each feature to form an isosceles triangle in the middle of the face. The researchers claim that this triangle is unique for every person, making it useful for face recognition in general and for face recognition with age variation in particular. Their system has some difficulty detecting facial components if the test images are not of frontal faces, making it inappropriate for real-time applications. In addition, the mathematical calculations require prior knowledge of the subjects' ages in both the test and probe images, which may not be feasible in some real-life scenarios. The system is not fully automated in that the face area must be cropped manually. However, the concept is straightforward and simple and the computational complexity is obviously low.

Drygajlo et al. [77] proposed a generalised Q-stack model consisting of age- and class-independent quality measures, along with scores from a baseline classifier, using local ternary patterns (LTP), which are an extension of local binary patterns that permit the use of a threshold constant to threshold image pixels. The use of LTP improves long-term class separation by introducing a multi-dimensional parameterised decision boundary in the score–age quality classification space, using a short-term enrolment model.

Xu et al. [78] proposed an age-invariant face recognition system based on the assumption that the Periocular area is the most age-invariant local area in the face and that it changes rather slowly over time. They summarised the following reasons for using the Periocular region to extract discriminative local facial features:

- The Periocular area is the most age-invariant facial region.
- Compared to global feature-based approaches, the representation of local features is considered robust to aging, illumination, and expression variations.
- Full face modelling for age invariance is a difficult task.
- The Periocular region changes only slightly over time because the shape and location of the eyes remain largely unchanged, while the mouth, nose, chin, and cheek are more susceptible to changes associated with loosening skin.

- The Periocular region has the most solid and most complex biomedical features on the human face [contour, eyeball, eyelids, and eyebrows, all of which can vary in shape, size, and colour].

They utilised the 68 facial landmark points that are given in FGNET to locate the eyes and then performed rotation and eye coordinate normalisation to horizontally align the left and right eyes with fixed eye coordinates for every image. The Walsh local binary pattern (WLBP) is used to extract the locally discriminative characteristics of the Periocular region. To find an optimal subspace within the Periocular region, they employ the unsupervised discriminant projection algorithm. To avoid computation complexity and speed up the WLBP, they us Walsh masks as convolution filters to approximate the Walsh–Hadamard transform. The researchers consider their system to be the best-performing algorithm for age-invariant face recognition using the FGNET database. However, a question arises as to whether the Periocular region would be found to have the same level of uniqueness if the system were tested over a very large database.

Mao et al. [79] proposed an age-invariant face verification method using a local classifier ensemble model. Their system is based on locating reference points on an extended active shape model. Faces are aligned forward. The researchers divide the faces into non-overlapping patches, and each group is further divided into several overlapping sub-patches. Local classifiers are then trained for each sub-patch and integrated to build an ensemble classifier in a semi-naïve Bayesian framework. This system needs global feature representation in addition to local feature representation to produce better feature representations of human faces.

Most recently, Bereta et al. [80] studied the performance with age variation of multiple local descriptors that are commonly used in face recognition. Those descriptors, when combined with Gabor magnitudes, were able to achieve higher accuracies than when they were working as stand-alone entities, particularly MBLBP, which is most stable when different age groups and ranks are considered. Recognition accuracies produced by descriptors combined with Gabor phases are significantly lower. The results show that local descriptors and Gabor wavelets can potentially be useful tools for facial recognition in the context of aging. The advantages of this approach derive from its robustness to changes in expression, luminance and pose provided by the Gabor wavelets. Furthermore, the approach does not need a training stage. However, this approach needs to be complemented with other methods to further increase its recognition accuracy. Furthermore, texture analysis is neglected in this approach, and the sizes of feature vectors could make the recognition process computationally expensive. **Table 3** summarises some of the previous research in age-invariant face recognition using non-generative approach.

Table 3. Age-invariant face recognition—proposed systems based on the non-generative approach.

Reference	Method	Dataset	(No of images, no of subjects)	Results (%)	Advantages of the system	Disadvantages of the system
Ramanathan	Bayesian age	Private	930	91.5	The proposed	The method does not

et al. [41]	difference classifier	passport photo dataset	images, 465 subjects		methods are effective in addressing age progression in human faces that have direct relevance to passport Image renewal applications.	account for shape variations in faces, thus it may not be effective for handling age progression in face images of children.
Singh et al. [72]	Age transformation algorithm	Private database + FGNET	1,578 images, 130 subjects	87.09	The proposed age transformation Algorithm effectively minimises the age difference between gallery and probe images.	-The proposed system requires further improvement to increase the accuracy for the 1- to 18-year age group. - The system has difficulty in dealing with facial aging along with variations in pose, expression, illumination, and disguise.
Biswas et al. [73]	Facial feature drift coherency	FGNET	1,002 images, 82	77.5	The method is relatively intuitive and simple.	Textural variations with aging that may be useful for matching age-separated images of adults were not taken into consideration.
Drygajlo et al. [74]	Linear ternary patterns (LTPs) and a generalised Q-stack aging model.	MORPH dataset1 MORPH dataset2	210 images, 42 subjects 900 images, 45 subjects	63.3 (baseline) 65.18 (SVM-lin) 64.14 (SVM-rbf)	-The use of LTP provides the advantages of invariance against illumination changes and computational efficiency and improved insensitivity to noise. -The proposed method allows for improved long-term class separation.	- LTP is not invariant under grey-scale transform of intensity values because its encoding is based on a fixed predefined thresholding.
Drygajlo et al. [77]	Q-stack classification	MORPH	280 images, 14 subjects	68.48 (Baseline) 88.78 (SVM-lin) 94.5 (SVM-rbf)	-The proposed method can automatically track the tendencies of the facial changes of a specific user as aging progresses. -The proposed technique	The proposed model assumes that several samples are available for building the Q-stack classifier for each subject, which is not always the case in real-life applications.

					permits reduction of the error rates below those of the baseline classifier.	
Xu et al.[78]	Extracting and analysing the periocular region	FGNET	1,002 images, 82 subjects	100	-The periocular region has the densest and most complex biomedical human features. -The periocular region changes only slightly over time. -Full face modelling for age invariance is complicated.	The system need to be validated over a larger database to test whether the periocular region has the same level of uniqueness.
Mao et al. [79]	Local classifier ensemble model	MORPH	Not specified	90	-Local features, rather than global features, are used to achieve dimension reduction. - A novel classifier ensemble framework based on a semi-naïve Bayesian method is introduced to integrate the local classifiers.	There is a need for global feature representation along with the local features to compose better feature representations of human faces.
Narsaria et al. [76]	Extracting a triangle of facial features	FGNET	100 images, 25 subjects	80	-The approach is simple and the computational cost is low. -The proposed method requires little processing time for each test image.	-The model requires prior knowledge of subjects' age in both test and gallery images, which may not be feasible in some real-life cases. -The method has difficulty when applied to non-frontal face images.
M. Bereta et al. (2013) [80]	Multiple local descriptors and Gabor wavelets	FGNET	1,002 images, 82 subjects	78	-Gabor features are robust against local distortions caused by variation in illumination, expression and pose, which exist in most of the FGNET images. - The approach does not require a training stage.	-Texture analysis is neglected. -The method needs to be complemented by methods that will further increase recognition accuracy. -Adaptation of appropriate aging models is needed -Gabor wavelets require high computational effort.

	-The use of WLD permits powerful representation of textures.	-The size of feature vectors could make the recognition procedure computationally expensive.

4 Face Aging Databases

Over the years, several face databases have been collected to help study the different problems associated with face recognition. Given the difficulty of compiling face datasets that encompass age-separated face images, there are very few publicly available datasets that specifically address facial aging versus datasets that address other problems in face recognition. There are three publicly available databases that consist of age-separated face image samples, namely, the MORPH Database [82], the FG-NET Aging Database [84], and the FERET Database [83]. Here, we provide a brief description of each of the three databases and their relevance to modelling facial aging.

- **FGNET database**

FG-NET contains 1,002 high-resolution colour and greyscale face images of 82 subjects from multiple races with a wide variation in lighting, expression, and pose. The image size is approximately 400 x 500 pixels. The age range of the subjects is from 0 to 69 years. The database contains 12 images per subject, on average [84].

- **MORPH database**

The MORPH Database [82] contains face images of adults taken at different ages. The database has been organised into two albums: MORPH Album 1 and MORPH Album 2. MORPH Album 1 contains 1,690 digitised images of 515 individuals ranging in age from 15 to 68 years. MORPH Album 2 contains 15,204 images of nearly 4,000 individuals. Apart from the face images, the database also contains meta-information that is critical to the study of age progression; include the ages, genders, ethnicities, heights and weights of the subjects.

- **FERET Database**

The FERET Database [83] is a comprehensive database that can be used to study multiple problems related to face recognition, such as variations in illumination, pose, and facial expressions. The database contains a few hundred age-separated face images of subjects. The age separations are 18 months or more. The FERET dataset characteristics pertaining to facial aging can be described as follows:

Gallery set: 1,196 images.

Duplicate I Probe set: 722 images of subjects whose gallery matches were obtained 0–1,031 days earlier.

Duplicate II Probe set: 234 images of subjects whose gallery matches were obtained 540–1,031 days earlier.

5 Conclusions

Research into facial aging and age-invariant face recognition algorithms and systems provide a comprehensive understanding of the problem of characterizing facial aging and the challenges facial aging poses in face recognition. Despite the progress made to date, there are some limitations to the previous research. Most of the systems that have been developed using the generative approach and have been based on building an aging model neglect the texture changes associated with adult aging. The performance of the few generative approach studies that have proposed aging models that account for shape and texture variations has not been sufficiently validated because of the insufficient number of training images involved in the experimental work. The performances of most of the systems that have been developed using the non-generative approach are adversely affected by factors such as illumination and pose variations. Systems that are able to achieve good recognition accuracies assume the availability of a large number of sample images for each subject, which is not always the case in real-life applications.

Our observations and future recommendations include the following. Because the face recognition systems that address the facial aging problem are used primarily in applications such as tracking criminals and/or terrorists, the error rates, in terms of false positive and false negative rates are very critical. In most of the research reviewed in this study, the error rates achieved by the systems proposed have not been reported, making it difficult to evaluate their performance in practical settings. Intensive research is needed to examine the age-invariant approaches and demonstrate their contributions to addressing the problem of facial aging in face recognition. Such research should include reporting of the error rates and accuracies associated with each approach, which will aid in clarifying the actual contribution of each approach to the field of age-invariant face recognition. As for the face aging datasets, it is obvious that there is a need for a dataset that represents a compromise between having a very large number of subjects and a large number of images for each subject with long age spans between the gallery images of each subject. Having such a dataset would be helpful in clearly demonstrating the diverse aging patterns for each subject. FGNET database is a well-organised dataset that is appropriate for research purposes because the set of images for each subject covers an age span from 0 to 69 years, but the number of subjects is relatively low. The MORPH database, on the other hand, is the largest publicly available face recognition database, but it does not include images from the infancy stage, and it has a relatively low number of images for most of the subjects.

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References

1. A. S. Tolba, A.H.E.-B., and A.A. El-Harby, Face Recognition: A Literature Review. International Journal of Information and Communication Engineering, 2006. 2:2
2. Charles Otto, H.H., and Anil Jain, How Does Aging Affect Facial Components? Springer-Verlag Berlin Heidelberg, 2012. 7584(ECCV 2012 Ws/Demos, Part II): p. 189–198.
3. Blanz, V., Vetter, T, Face recognition based on fitting a 3d Morphable model. IEEE Trans. PAMI, 2003. 25: p. 1063–1074
4. Zhang, X., Gao, Y., Face recognition across pose: A review. Pattern Recognition, 2009. 24: p. 2876–2896
5. Lanitis, A. Facial Biometric Templates and Aging: Problems and Challenges for Artificial Intelligence. In AIAI-2009 Workshops 2009.
6. Lanitis, A., Comparative Evaluation of Automatic Age Progression Methodologies. EURASIP Journal on Advances in Signal Processing, 2008.
7. Sydney R. Coleman, M.R.G., the Anatomy of the Aging Face: Volume Loss and Changes in 3-Dimensional Topography. An Aesthetic S Urgery J Ournal 2006.
8. M. S. Zimbler, M.K., J. R. Thomas, Anatomy and Path physiology of Facial Aging. Facial Plastic Surgery Clinics of North America, 2001. 9: p. 179-187.
9. Iscan, M.Y., Global forensic anthropology in the 21st century. Forensic Science International, 2001. 117(1-2): p. 1-6.
10. Taylor, K.T., Forensic Art and Illustration. 2001: Boca Raton: CRC Press.
11. Behrents, R.G., an Atlas of Growth in the Aging Craniofacial Skeleton. Craniofacial Growth Series, ed. A. Arbour. 1985, Michigan.
12. Dayan, N., Skin Aging Handbook: Market Perspectives, Pharmacology, Formulation, and Evaluation Techniques, ed. A.W. Press. 2008.
13. L. S. Mark, R.E.S., and J. B. Pittenger, Natural constraints, scales of analysis, and information for the perception of growing faces. In Social and Applied Aspects of Perceiving Faces, ed. N.L.E. Mahwah. 1998.
14. Eric Patterson, A.S., Midori Albert, and Karl Ricanek. Comparison of Synthetic Face Aging To Age Progression by Forensic Sketch Artist. In the seventh IASTED international conference visualization, imaging, and image processing. 2007.
15. M.A. Taister, S.D.H., and H. Borman, Comments on Facial Aging in Law Enforcement Investigation, V.I.S.I.a.P.G. Unit, and Editor. 2000, Federal Bureau of Investigation Washington, DC.
16. D. De Carlo, D.M., and M. Stone. An Anthropometric Face Model Using Variation Techniques. In 25th Int'l Conf. Computer Graphics and Interactive Technique. 1998.
17. Jain, X.L.a.A.K. Deformation modelling for robust 3d face matching. In IEEE Conf. Computer Vision and Pattern Recognition (CVPR). 2006. Washington, D.C.
18. U. Park, H.C., and A. K. Jain. 3d model-assisted face recognition in video. In 2nd Canadian Conference on Computer and Robot Vision. 2005. Washington, D.C.
19. Parke, F.I. Computer generated animation of faces. In ACM National Conference. 1972.
20.Parke, F.I., A Parametric Model of Human Faces. 1974, University of Utah: Salt Lake City.
21.Paul Viola, M.J., Robust real-time face detection. International Journal of computer vision, 2004. 57(2): p. 137-154.
22.N.Magneneat-Thalmann, H.M., M. Angelis, and D. Thalmann, Design transformation and animation of human faces. Visual Computer, 1989. 5: p. 32–39.
23.Yan, K.-M.L.a.H., An Analytic-to-Holistic Approach for Face Recognition Based on a Single Frontal View. PAMI, 1998. 2-7: p. 673-686.
24.Vetter, V.B.a.T. A morphable model for the synthesis of 3D-faces. in SIGGRAPH 99 Conference3 1999. Los Angeles.

25.Liu, Z., Zhang, Z., Jacobs, C. and Cohen, M. Rapid modeling of animated faces from video. in 3rd International Conference on Visual Computing. 2000. Mexico City: The Journal of Visualization and Computer Animation.
26.Y. X. Hu, D.L.J., S. C. Yan, Lei Zhang, H.J. Zhang. Automatic 3D Reconstruction for Face Recognition. in FG2004. 2004.
27.Y. Wang, C.C., and Y. Ho, Facial Feature Detection and Face Recognition from 2D and 3D images. Pattern Recognition Letters, 2002. 23: p. 1191-1202.
28.K. I. Chang, K.W.B., and P. J. Flynn, An Evaluation of Multimodal 2D+3D Face Biometrics. IEEE Trans. on Pattern Analysis and Machine Intelligence, 2005. 27.
29.A. M. Bronstein, M.M.B., R. Kimmel, Three dimensional face recognition. International Journal of Computer Vision 2005. 64/1: p. 5-30.
30.X. Lu, a.A.K.J. Integrating Range and Texture Information for 3D Face Recognition. in IEEE WACV. 2005. Breckenridge, Colorado
31.W.-Y. Zhao, R.C., P. J. Phillips, and A. Rosenfeld, Face recognition : A literature survey. ACM Computing Surveys, 2003: p. 399–458.
32.Lobo, Y.H.K.a.N.d.V., Age classification from facial images. Computer Vision and Image Understanding, 1999. 74: p. 1–21.
33.A. Lanitis, C.D., and C.Christodoulou, Comparing different classifiers for automatic age estimation. IEEE Transactions on Systems, Man and Cybernetics - Part B, 2004. 34(1): p. 621–628.
34.Gandhi, M., A method for automatic synthesis of aged human facial images. 2004, McGill University.
35.X. Geng, Z.-H.Z., Y. Zhang, G. Li, and H. Dai. Learning from facial aging patterns for automatic age estimation. in the 14th annual ACM international conference on Multimedia. 2006.
36.Chellappa, N.R.a.R. Modeling Shape and Textural Variations in Aging Faces. in Automatic Face & Gesture Recognition, 2008. FG '08. 8th IEEE International Conference. 2008.
37.H. Ling, S.S., N. Ramanathan, and D. Jacobs. . A study of face recognition as people age. in ICCV. 2007. Rio de Janeiro, Brazil.
38.E. Patterson, A.S., M. Albert, and K. Ricanek. Aspects of age variation in facial morphology affecting biometrics. in BTAS. 2007. Washington D.C.
39.J. Suo, F.M., S. Zhu, S. Shan, and X. Chen. A multi-resolution dynamic model for face aging simulation. in CVPR. 2007. Minneapolis, U.S.A.
40.Chellappa, N.R.a.R. Modeling age progression in young faces. in CVPR. 2006. New York, U.S.A.
41.Chellappa, N.R.a.R., Face verification across age progression. IEEE Transactions on Image Processing, 2006. 11: p. 3349–3361.
42.Gandhi., M., A method for automatic synthesis of aged human facial images. 2004, McGill University.
43.A. Lanitis, C.J.T., and T. F. Cootes. , Toward automatic simulation of aging effects on face images. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002. 24(4): p. 442–455.
44.B. Tiddeman, D.M.B., and D. Perret. Prototyping and transforming facial texture for perception research. in Computer Graphics and Applications, IEEE. 2001.
45.Perrett, M.B.a.D.I., Perception of age in adult Caucasian male faces: computer graphic manipulation of shape and color information. Journal of Royal Society, 1995. 59: p. 137–143.
46.Marr, D., Vision, ed. W.H. Freeman. 1982, San Francisco, CA.
47.Gibson, J.J., The Senses Considered as Perceptual Systems. 1966, Boston: Houghton Mifflin.
48.O'Toole, A.J., Cognitive and Computational Approaches to Face Recognition. Oxford Handbook of Face Perception. 2012.

49.Jinli Suo, S.-C.Z., Shiguang Shan, and Xilin Chen, A Compositional and Dynamic Model for Face Aging. IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE, 2010. 32-3.
50.B.P. Tiddeman, M.R.S., and D.I. Perrett. Towards Realism in Facial Prototyping: Results of a Wavelet MRF Method. in 24th Conf. Theory and Practice of Computer Graphics. 2006.
51.J. Wang, Y.S., G. Su, and X. Lin. Age Simulation for Face Recognition. in 18th Int'l Conf. Pattern Recognition. 2006.
52.U. Park, Y.T., and A.K. Jain. Face Recognition with Temporal Invariance: A 3D Aging Model. in Eighth Int'l Conf. Automatic Face and Gesture Recognition. 2008.
53.Zheng, Y.F.a.N., M-Face: An Appearance-Based Photorealistic Model for Multiple Facial Attributes Rendering. IEEE Trans. Circuits and Systems for Video Technology, 2006. 16-7: p. 830-842.
54.Z. Liu, Z.Z., and Y. Shan, Image-Based Surface Detail Transfer. IEEE Computer Graphics and Applications, 2004. 24-3: p. 30-35.
55.E. Patterson, K.R., M. Albert, and E. Boone. Automatic Representation of Adult Aging in Facial Images. in Sixth IASTED Int'l Conf. Visualization, Imaging, and Image. 2006.
56. Ling, J.W.a.C. Artificial Aging of Faces by Support Vector Machines. in 17th Canadian Conf. Artificial Intelligence. 2004.
57.T.J. Hutton, B.F.B., P. Hammond, and H.W.W. Potts, Estimating Average Growth Trajectories in Shape-Space Using Kernel Smoothing. IEEE Trans. Medical Imaging, 2003. 22-6: p. 747-753.
58.A.C. Berg, F.J.P.L., and M. Gonzalez. A Facial Aging Simulation Method Using Flaccidity Deformation Criteria. in 10th Int'l Conf. Information Visualization. 2006.
59.Wang, F.J.a.Y. Facial Aging Simulation Based on Super Resolution in Tensor Space. in 15th Int'l Conf. Image Processing. 2008.
60.Lanitis, A., Comparative Evaluation of Automatic Age-Progression Methodologies. EURASIP J. Advances in Signal Processing, 2008. 8-2: p. 1-10.
61.Huang, Y.F.a.T.S., Human Age Estimation with Regression on Discriminative Aging Manifold. IEEE Trans. Multimedia, 2008. 10-4: p. 578-584.
62.G. Guo, Y.F., C.R. Dyer, and T.S. Huang, Image-Based Human Age Estimation by Manifold Learning and Locally Adjusted Robust Regression. IEEE Trans. Image Processing, 2008. 17-7: p. 1178-1188.
63.S. Yan, H.W., X. Tang, and T.S. Huang. Learning Auto-Structured Regressor from Uncertain Nonnegative Labels. in 11th Int'l Conf. Computer Vision. 2007.
64.J. Suo, T.W., S.C. Zhu, S. Shan, X. Chen, and W. Gao. Design Sparse Features for Age Estimation Using Hierarchical Face Model. in Eighth Int'l Conf. Automatic Face and Gesture Recognition. 2008.
65.X. Geng, Z.Z., and K. Smith-Miles, Automatic Age Estimation Based on Facial Aging Patterns. IEEE Trans. Pattern Analysis and Machine Intelligence, 2007. 29-12: p. 2234-2240.
66.Unsang Park, Y.T.a.A.K.J., Face Recognition with Temporal Invariance: 3D Aging Model, in Automatic Face & Gesture Recognition, 2008. FG '08. 8th IEEE International Conference . 2008.
67.Unsang Park, Y.T., Anil K. Jain, Age-Invariant Face Recognition. IEEE Transactions On Pattern Analysis And Machine Intelligence, 2010. 32-5.
68.Haibin Ling , S.S., Narayanan Ramanathan, and David W. Jacobs, Face Verification Across Age Progression Using Discriminative Methods. IEEE Transactions On Information Forensics And Security, 2010. 5-1.
69.H. Chen, P.B., and D. Jacobs. In search of illumination invariants. in IEEE Conf. Computer Vision and Pattern Recognition (CVPR). 2000.
70.Kambhamettu, G.M.a.C., Age Invariant Face Recognition Using Graph Matching., in Theory Applications and Systems (BTAS) 2010, Fourth IEEE International Conference.

71.Zhifeng Li, U.P., and Anil K. Jain, A Discriminative Model for Age Invariant Face Recognition. IEEE Transactions On Information Forensics And Security, 2011. 6- 3.
72.Chellappa, T.W.a.R. Age Invariant Face Verification with Relative Craniofacial Growth Model. in ECCV 2012. 2012: Springer-Verlag Berlin Heidelberg
73.Richa Singh, M.V., Afzel Noore, and Sanjay K. Singh. Age Transformation for Improving Face Recognition Performance. in PReMI 2007. 2007: Springer-Verlag Berlin Heidelberg
74.Soma Biswast, G.A., Narayanan Ramanathan, and Rama Chellappa, A Non-generative Approach for Face Recognition Across Aging, in BTAS 2008. 2nd IEEE International Conference. 2008.
75.Andrzej Drygajlo, W.L.a.K.Z., Q-Stack Aging Model For Face Verification, in 17th European Signal Processing Conference (Eusipco 2009). 2009.
76.Cui Meng, J.L., and Yap-Peng Tan, A Comparative Study of Age-Invariant Face Recognition with Different Feature Representations, in 11th Int. Conf. Control, Automation, Robotics and Vision 2010: Singapore.
77.Ankit Kumar Narsaria, H.R., Pramit Dutta, Face Recognition With The Progression Of Age Using Face Triangle Formation. International Journal of Research in Engineering, IT and Social Sciences 2012. 2(11).
78.Andrzej Drygajlo, W.L., and Hui Qiu Face Recognition in Score-Age-Quality Classification Space. in BioID 2011. 2011: Springer-Verlag Berlin Heidelberg.
79.Felix luefei-Xu, K.L., Marios Savvides, Tien D. Bui, and Ching Y. Suen. Investigating Age Invariant Face Recognition Based on Periocular Biometrics. in International Joint Conference on Digital Object 2011.
80.Xiao-Jiao Mao, Y.-B.Y., Ning Li, Yao Zhang, Age-Invariant Face Verification Based on Local Classifier Ensemble, in 21st International Conference on Pattern Recognition (ICPR 2012) 2012: Tsukuba, Japan.
81.Bereta, M., Local descriptors in application to the aging problem in face recognition. Pattern Recognition 2013.
82.Ricanek, A.M.A.a.K., The MORPH database: Investigating the effects of adult craniofacial aging on automated face-recognition technology. Forensic Science Communications, 2008. 10-2.
83.P. J. Phillips, H.M., and P. J. R. S. A. Rizvi, The FERET evaluation methodology for face recognition algorithms. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2000. 22-10: p. 1090–1104.
84.FG-Netagingdatabase.