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CRANIOFACIAL AGING

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Abstract: Face recognition is one of the most favored techniques used in the field of biometrics. Despite many of the advanced methods that have been developed, face recognition is still challenged by many factors such as illumination, pose, and other real-world conditions such as a temporal difference in training and classification data (mainly images). As such, normal adult aging is an important factor to be considered in the development and evaluation of face-recognition systems. To date, little progress has been made in developing techniques that are robust to age-progression in individuals. Two of the main reasons for minimal development in this area are an incomplete understanding of the factors that influence the changing appearance of the face during aging and a lack of relevant longitudinal face corpora required for development and evaluation. This article provides a summary understanding of the factors and process innate to craniofacial morphology of the face during the period of adult aging and also reviews recent biometric-related work on aging of the human face. Additionally, this work can be used to inform practitioners who conduct human-based analysis on longitudinal face images for identity verification.

Keywords: age-progression; aging; face recognition; biometrics; craniofacial morphology; longitudinal study

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1 SCIENTIFIC OVERVIEW

Q2 Medical and forensic studies have been conducted for quite some time on various aspects of human aging and its relation to changes in the face [1–4], but few studies have addressed the effects of aging on face biometric technologies. There have been a few studies conducted recently with regards to modeling the effects of growth and development (i.e. the stage from birth to maturation) for application to face recognition technologies [5–10]. Although similar approaches to studying growth and development and adult aging may yield improvements in biometric technologies, the two processes are distinct, and therefore, should be studied separately for more accurate modeling of the underlying processes [3, 4].

Some work has been conducted concerning simulation of aging in facial images or models, considering a few different approaches. One approach is biomechanical simulation, and work in this area has included a layered facial simulation model for skin aging with wrinkles [11], an analysis–synthesis approach to aging the orbicularis muscle in virtual faces [12], and a flaccidity-deformation approach [13]. Anthropometric deformation approaches have also been attempted for both adult aging [14] and growth and development [15]. In one of recent works [16], a twofold approach toward modeling facial aging in adults is proposed. In this work, a shape transformation model that is formulated as a physically based parametric muscle model that captures the subtle deformations facial features undergo with age is developed. Next, an image gradient–based texture transformation function that characterizes facial wrinkles and other skin artifacts often observed during different ages is developed. Other approaches have also simulated aging through direct image manipulation of shape and texture, mainly for testing human perception [17, 18]. A summary of existing research on craniofacial aging, age-progression, and face biometric techniques that address the effects of aging directly are presented in the following sections.

1.1 Craniofacial Aging: Findings in Anthropology and Forensics

The craniofacial region of a human is where, effects of aging that would significantly impact human or computer recognition of individuals occurs. These changes include both the bony portion of the head as well as the overlying soft tissues that produce the external appearance of one's face. There is a large body of literature concerning this facial morphology due to aging that may be referenced to learn aspects that should be considered for face recognition technologies [4, 19, 20].

Our modern approach to studying age-related changes to the craniofacial complex can be traced back to D'Arcy Thompson's now classic work, first published in 1917—*On Growth and Form*—in which he explained shapes in the biological world in part through mathematics [21]. Contemporary studies indeed suggest that cardioidal strain transformation, a nonlinear topographical transformation, may be a reasonable mathematical model through which to observe major changes in craniofacial shape affected by growth [22, 23]. However, cardioidal strain transformations cannot account for other aging features such as hair, skin elasticity and texture, adipose tissue, nose, ears, eyes, and lips [24]; therefore, its importance in recognizing faces as they age should not be overestimated [25]. While three-dimensional shape changes may affect perceptions of aging, there is also evidence to suggest that age perception is highly dependent on internal facial features as well—eyes, lips, nose, and ears [26]. Indeed, the distinction between feature-based and configurational information is one of the ultimate challenges in face recognition [26]. Key features changing with adult age are noted below.

Degenerative soft tissue changes and small shifts in skeletal form ultimately affect the appearance of the face during aging. The skeletal changes include cranial expansion, anterior face-height increase, and jaw shrinkage [20]. Soft tissue appearance is affected by decreasing muscle tone or atrophy, diminishing collagen and elastin, and skin wrinkling and sagging. Along with these natural changes that occur with aging, there are other aspects that affect facial appearance over time. Of these, photoaging is one of the most significant—largely impacting fair-skinned individuals and those residing in sunny regions [4]. Other major factors include ancestry, gender, health and disease, tobacco and drug use, diet, stress-related sleep deprivation, biomechanical factors, gravity, and hyperdynamic facial expressions [4, 20]. In addition, there are factors that can exacerbate age-related changes such as weight loss due to illness, drug use, and/or some medications [4, 19].

These changes are not consistent but vary in rate over adulthood. As expected, fewer changes generally occur in the twenties, accelerating a little in the thirties, and increasing even more in the forties and fifties—typically the period of greatest change. This period of greater morphology is fairly consistent across race and gender. Past the fifties, the changes that have begun increase significantly and other associated degenerative affects may appear.

Figure 1 illustrates the changes in an aged female with annotated points. Changes to note beginning in the twenties and thirties include horizontal creases in the forehead (areas 1 and 2), slight drooping of the eyelids (area 6 and 9), nasolabial lines or "laugh lines" (areas 16 and 17), lateral orbital lines or "crow's feet" (area 7), circumoral striae (which are lines around the mouth) (areas 18 and 20), hollowing of the cheek (around area 15), decrease in upper lip size (area 21), and retrusion (which is a backward movement of the upper lip that is more apparent in females) [4, 19, 20].

Through the adult aging process these changes become more noticeable, and by or around the age of 50, there are other changes that have begun including the appearance of fine lines, and thinning and sagging of skin as shown in Figure 2. Skin also becomes rougher, drier, and shows loss of tone and elasticity. This combined with atrophy in corrugator and orbicularis muscles can affect facial appearance greatly. Wrinkles appear on the neck, and discolorations in skin may begin to appear. Loss of hair and depigmentation may occur. Hair may also grow in areas that previously had little or no growth [4, 20].

In general, trends occur that affect facial size as well. Small skeletal changes in height and width affect the outer appearance of the soft tissue. Nose height and length increases, and ear length increases. Mouth width also increases. In very aged people, faces may appear smaller due to overall degeneration of the boney substructure (craniofacial complex) and tissue degeneration.

Table 1 summarizes the soft tissue and hard tissue changes that occur at various age spans [3].

2 CRITICAL NEEDS ANALYSIS

Face recognition has been a key biometric research area for more than a decade. This technology has had mixed, almost disappointing, results when applied in commercial venues [27–29]. Nonetheless, robust face recognition systems are needed to meet the

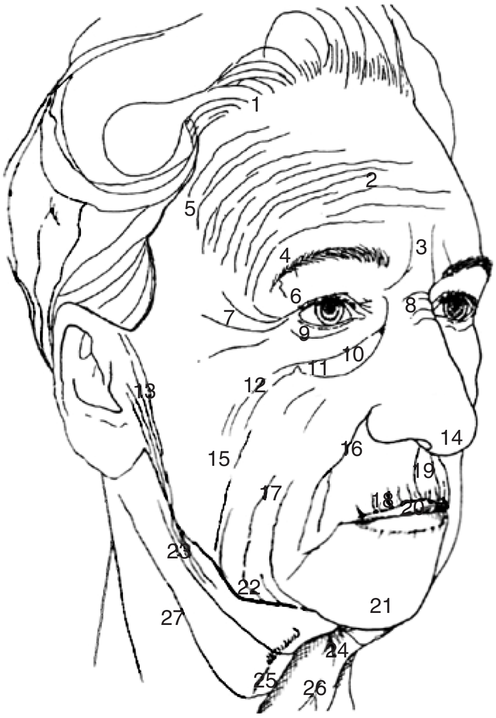

FIGURE 1 Annotated diagram of craniofacial morphology.

demands of intelligence agencies, military, and, more broadly, homeland security. Face recognition systems used for identification or watch lists require enrollment, which is the process of learning known faces. The performance of these systems deteriorates after a few years unless the system is updated with current faces of the known subjects. The degradation of performance of these systems has been demonstrated, but not studied in depth, as far back as the original FERET evaluations [30]. They were also further highlighted in FRVT 2002 [31]. The paucity of research on this topic can be summarized as
Q3 (i) the algorithm developers had little to no understanding of the complete biomechanical processes that affect facial aging and (ii) there are only a few publicly available longitudinal face databases. The following section details the known longitudinal databases and summarizes the results of recent work in quantifying the effects of age-progression and automatic synthesis of adult aging in facial images.

2.1 Longitudinal Face Databases

Q4 The FERET, FRVT, and FRGC to further biometrics research and each has created vast data corpora to facilitate the analysis and evaluation of various biometrics. Furthermore, each program contains face databases designed to meet the mandate of each challenge. The FERET face database (1994), which continues to be used by researchers worldwide, contains a set of longitudinal images in its Duplicate I and Duplicate II data sets. The Duplicate I probe set holds 722 images whose matches were taken between 0 and 2.8 years after the match. The median is 2 months and the mean is 8.25 months. The Duplicate II probe set contains 234 images from subjects whose match was taken between 540

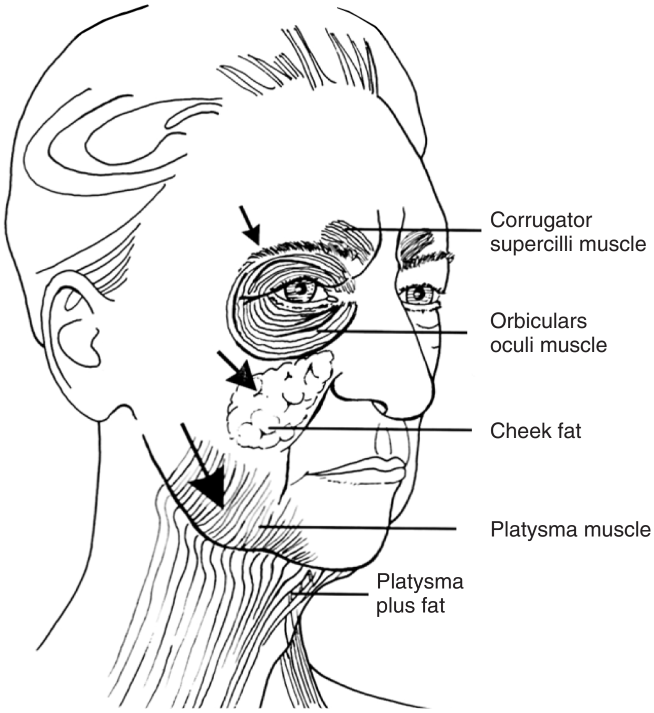

FIGURE 2 Illustration of aging: impacts on soft tissue (musculature and skin) demonstrating
Q5 wrinkling and muscle sagging.

and 1031 days beforehand. The median is 1.5 years and the mean is 1.7 years. The challenge of using FERET is sparseness of subjects, unknown ages, and diversity of gender and ethnicity. The FRVT 2002 database was comprised of longitudinal images of subjects with some ethnic diversity, but this was not released for general public research as was the FERET. Additional information can be obtained on this database from the website (www.frvt.org). The FRGC primary objectives did not include the problem of age-progression or gallery-probe acquisition differences.

Q6 The FG-NET Aging Database [32] constructed by Andreas Lanitis at Cyprus College, is constructed from scanned photographs provided by volunteers. The photographs range from childhood to senescence of 82 subjects under various pose and facial expressions. The database does not provide researchers with important parameters like ethnicity, height, or weight.

The Craniofacial Morphological Face Database, MORPH, is a longitudinal face database developed for researchers investigating all facets of adult age-progression [33]. The MORPH database includes metadata on the face images within the database: subject's ethnicity, height, weight, gender, and age. Figure 4 is a sample of two subjects from the database highlighting appearance changes of adult faces. The database is partitioned into two albums, Album 1 and Album 2. Album 1 consists of 1690 images of 628 subjects that were scanned from photographs taken as far back as the 1960s. Album 2 has over 55,608 digital images of 13,673 subjects which consist of males and females of the Caucasian, Asian, Hispanic, and African ethnic groups; however, there are very few Asian and Hispanic samples. Detailed statistics are shown in Tables 2 and 3. The MORPH database is an ongoing project in the Computer Science

TABLE 1 Adult Hard and Soft Tissue Age-related Changes

Approximate Age Range (years)	Likely Bony Change	Probable Soft Tissue or Facial Appearance Effect
20–30	Slight craniofacial skeletal growth	Upper eyelid drooping begins
	Slight anterior (mostly lower) face height *increase*	Eyes appear smaller
		Nasolabial lines begin to form
	Mandibular length increase	Lateral orbital lines begin to form
		Upper lip *retrusion* begins in females
30–40	*Dentoalveolar* regression suggesting eruptive movement of teeth	*Circumoral striae* begin to form
		Lines begin to form from lateral edges of nose *to* lateral edges of mouth.
	Maxillary *retrusion* progressing, contributing to *nasolabial* folds	
	Mandibular length increase	Upper lip thickness decreasing
40–50	Craniofacial skeletal remodeling progresses	Facial lines and folds continue to increase in depth
	Dental alveolar regression and dental eruption progressing	Nose and chin positioning affected as dental arch lengths decrease
	Maxillary and *mandibular* dental arch lengths decreasing	Most profound morphological changes of the head, face, and neck are evident
50–60	Craniofacial remodeling continues	Facial lines and folds continue to increase in depth.
	Cranial thickness likely unchanging	
	Alveolar bone remodeling	Protuberance of nose and ears due to greater craniofacial convexity
	Possible dental attrition affecting vertical face height	
<60	Decrease in craniofacial size	Protuberance of nose and ears continues
	Greater craniofacial convexity (excluding maxilla and mandible)	Concave appearance in cheek hollows due to alveolar bone remodeling
	Possible *temporomandibular* joint arthritis and joint flattening	
	Alveolar bone remodeling continues	Diminished jaws

Department at the University of North Carolina Wilmington and can be requested from www.faceaginggroup.com.

2.2 Effect of Adult Aging on a Standard Face Recognition Technique

The work of Ricanek and Boone 2005 [34] was an early attempt to quantify the effects of normal adult aging, age-progression, on a face recognition technique. In this work, the authors sought to quantify the impacts of aging against the standard PCA-face recognizer as implemented in the Colorado State University's Face Identification and Evaluation System (FIES). The FERET and MORPH databases were used for the evaluation. MORPH album 1 was used which contained large longitudinal images of more than 500 subjects

TABLE 2 Statistics for Morph Album 1

General		Age Statistics (yr)				
Number of Subjects	Number of Images	Minimum	Maximum	Average	Median	SD
515	1690	16	68	27.28	26	8.65

Morph Album 1: Number of Facial Images by Gender and Ancestry

	Americans of African Descent	Americans of European Descent	Americans of “Other” Descent	Total
Male	1037	365	3	1405
Female	216	69	0	285
Total	1253	434	3	1690

Morph Album 1: Number of Facial Images by Decade of Life Categories (yr)

	<18	18–29	30–39	40–49	50+	Total
Male	142	803	345	93	22	1405
Female	15	182	70	18	0	285
Q7 Total	157	985	415	111	22	1690

whose images were scanned from photographs. The largest span was 20.3 years and the average was 6.45 years.

The work concluded that there was a statistically significant degradation in rank-N performance as evaluated as a function of age difference between enrolled and probe. To this end, the researchers were able to generate a function of performance loss using logistic regression. Table 4 shows the results of the logistic regression on correct classification on the time-differenced images. The table illustrates that the time difference is an important factor in determining the recognition rate with a p value < 0.0001. Table 4 also shows the odds ratio associated with a 1 year increase in time between the enrolled image and the test (probe) image such that a 1 year increase would result in a rank-N performance decay of 0.6707. Figure 3 shows a graph of this relationship across time for rank 1 and Figure 4 illustrates the relationship for rank 5.

2.3 Face Recognition Using Synthetic Facial Aging

One of the several reasons that make testing variation in human faces due to aging, a difficult task, is data collection. Current face databases suffer from small number of subjects, less than a few hundred, and/or small number of or inconsistent age spans for subjects. There has been indication, though, that face recognition technologies are not well suited to perform invariantly across images of the same individual at different ages [6, 8]. As discussed in the previous section, the MORPH database has been developed to help research improvements for face technologies across a wide span of age with this in mind. It has been used to make some initial tests of face recognition performance across wide spans of age samples [8]. A few other studies have also begun to investigate the possible effects of age and aging-related variation in the human face-to-face recognition technologies [5–10]. All of these initial studies have concluded that there is the possibility

TABLE 3 Statistics for Morph Album 2

General		Age Statistics (yr)				
Number of Subjects	Number of Images	Minimum	Maximum	Average	Median	SD
13,673	55,608	18	77	32.69	33	10.9

Morph Album 2: Number of Facial Images by Gender and Ancestry

	Americans of African Descent	Americans of European Descent	Americans of "Other" Descent	Total
Male	37,093	8119	1845	47,057
Female	5803	2617	131	8551
Total	42,896	10,736	1976	55,608

Morph Album 2: Number of Facial Images by Decade of Life Categories (yr)

	<18	18–29	30–39	40–49	50+	Total
Male	2964	17,728	12,587	10,248	3530	47,057
Female	373	2783	2924	2017	454	8551
Total	3337	20,511	15,511	12,265	3984	55,608

TABLE 4 Logistic Regression Parameters: Longitudinal Difference MORPH Training and FERET Training

Rank	Training	Time Difference	Standard Error	p value	Odds Ratio
1	MORPH	−0.39941	0.07429	<0.0001	0.6707
	FERET	−0.36261	0.06714	<0.0001	0.6958
5	MORPH	−0.35702	0.05291	<0.0001	0.6997
	FERET	−0.33250	0.04983	<0.0001	0.7171

of significant degradation on the methods tested. Further study will need to expand these tests to very recent developments in face recognition technology that have shown significant performance increases in areas other than aging. Although it is still not known completely to what extent aging affects face-based biometric technologies, it is certain that it does have a strong impact on the appearance of the face and likely on most face recognizers.

Although the overarching theme is to develop robust, and to this end insensitive, face-based biometrics to the problem of age-progression the practical approach appears to be the development of synthesized imagery for enhancement of current methods. Intelligently crafted synthetic images may be used to augment training galleries or be used to manipulate current test images to improve performance in a variety of areas. This approach is broadly known as *template aging* via generative synthetic templates.

Orlans et al. demonstrated augmenting FRVT 2000 findings for pose and temporal experiments by support with synthetic face image galleries using Singular Inversions' FaceGen software [35] and the Viisage [36] FaceTools commercial face recognition

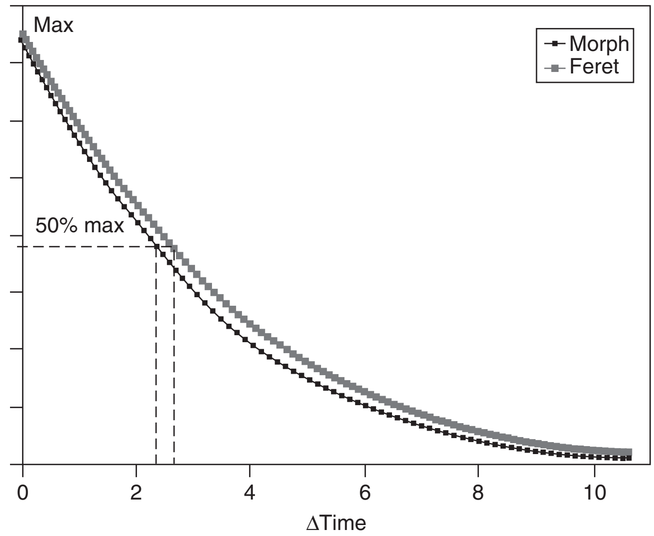

FIGURE 3 Probability of rank 1 recognition performance against time span (years) between enrolled and probe image. Logistic regression was used to formulate the model and projected over a time span of 10 years (FERET projection used both Duplicate I and Duplicate II partitions)

packages. They achieved a performance increase across pose variation tests by use of the synthetic images, and they demonstrated the individuality of the images in the synthetic gallery, but they also mentioned that it may be difficult to validate large galleries of synthetic faces. Also, 50 random faces were used and "aged" from 20 to 60 in 5-year increments with FaceGen [6]. FaceGen builds 3D faces synthetically using methods similar to those in [37] and allows for a gradient-based shifting of facial features, including age, but the statistical validity of these is not confirmed. With 128 principal components computed from 300 face scans, there may not be enough representation of aging among the population scanned, particularly across individuals to indicate idiosyncratic modes of aging [38]. Orlans et al. did mention that the statistical significance of this approach may be light but that recognition results degraded over "time" as represented by the synthesized test images.

Zhang et al. attempted to use a texture synthesis approach to correct for pose and illumination effects that degrade face recognition performance. Combined with a generic 3D face model and single frontal views, virtual views under different poses and illumination conditions were synthesized and used to augment the training gallery in a PCA-based recognizer and achieved a significant improvement in recognition accuracy across pose and illumination variations [39].

Lanitis and Taylor as well as Wang et al. have both conducted tests over the use of aging functions to improve recognition performance. Both of these cases, however, considered images from human growth and development (birth to 18, 19–30 in the first case, and unknown in the second case), not specifically adult aging—a different period with different aspects and rates of change as represented in the anthropological literature. Growth and development has larger scale changes of structure as bones shift during growth. Adult aging in general has smaller structural shifts for a long period of time marked by larger changes of textural information in images. The system used by Lanitis and Taylor estimates the age of a test image and parametrically shifts it to the mean

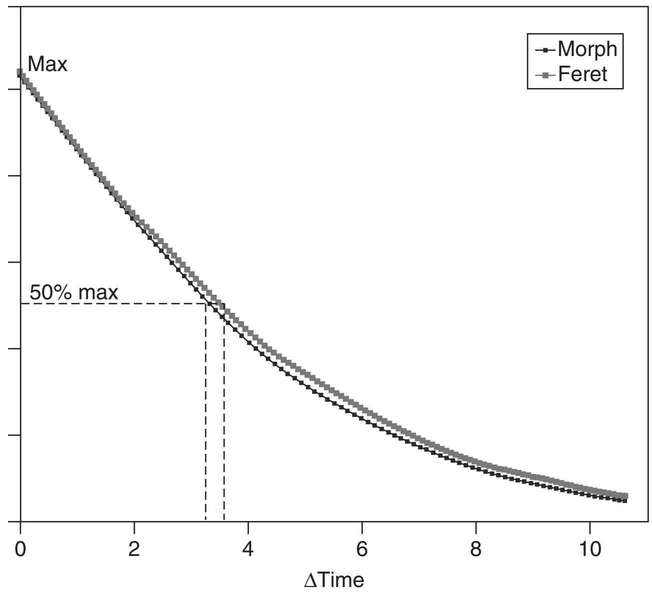

FIGURE 4 Probability of rank 5 recognition performance against time span (years) between enrolled and probe image. Logistic regression was used to formulate the model and projected over a time span of 10 years (FERET projection used both Duplicate I and Duplicate II partitions).

age of those represented in training [5]. Wang et al. appear to have used images from both growth and development and adult aging (a mean of 15-year age representation over 60 individuals, although the exact range of ages is not specified) and generate feature vectors of test faces at different ages [40]. Both cite improved performance in recognition, the first using an active-appearance-model (AAM)-based recognizer and the second a PCA-based recognizer. We have conducted brief initial tests indicating similar results. On a small subset of the MORPH database, with individual ages ranging from 18 to 40, PCA-based recognition was tested by augmenting the training gallery with "aged" images to match the current age of a test subject. Also, current test images were "de-aged" to match the range of ages of the individuals when gallery photos were taken. Although it was a very small test, the "de-aging" of the test images appeared to perform best for the given setup [9]. All of these initial studies have indicated a potential in some use of synthesized face information to improve biometric techniques.

We have recently conducted two initial studies using AAM-based approaches to synthetically age progressing and regressing images to represent adult aging effects to the face [41]. The first contained a small subset of the MORPH database [33]. Such is necessary to consider constructing individual or idiosyncratic models of face aging versus generalized models which could be based on large databases of individuals of a variety of ages.

In the first setup, images from 9 individuals over a roughly 20-year period were used along with a set of 65 landmarks (which were mostly a superset of the anthropometric landmarks made popular by Farkas), shown in Figure 5, to construct an AAM with 30 parameters and representations of an aging estimation function and aging-lookup table similar to that presented in [42] but geared specifically toward adult aging. More details concerning the first tests are presented in [9]. A new image that will be progressed or regressed has its AAM parameters shifted by a difference of parameters taken from the

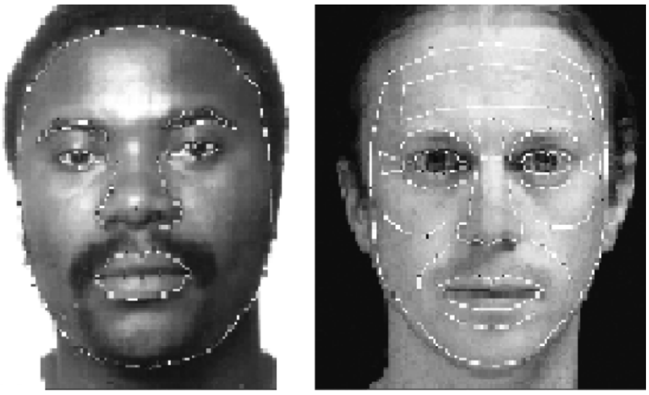

FIGURE 5 Landmarks used in first and second setups.

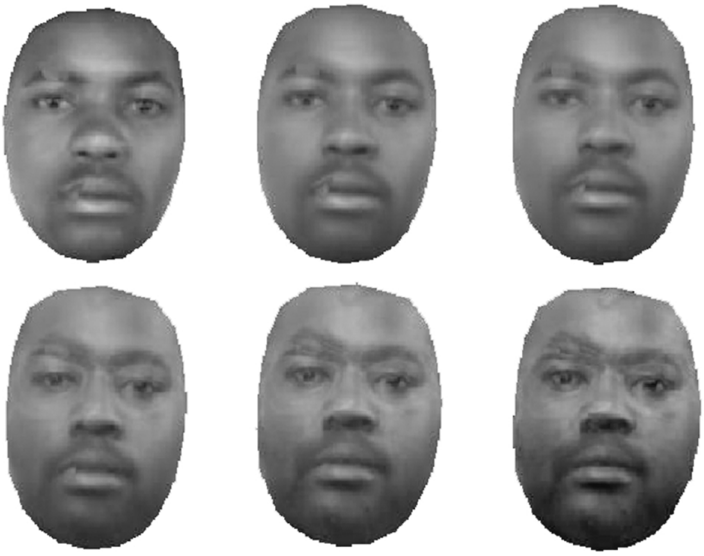

FIGURE 6 Average faces over age-progression with first setup, from age 18 to 40.

difference of the average age parameters in the lookup table generated by Monte Carlo simulation [9, 42]. Examples of the average age-progression as represented by the lookup table are shown in Figure 6.

The second setup was designed to emulate a forensic sketch artist's approach to age-progression and was built with 99 images from a family, including young images of an individual along with images of parents and grandparents from the same family. One hundred and sixty one landmarks, also shown in Figure 5, were used to attempt to better track specific regions of aging in the face, and 55 AAM parameters were used, retaining 98% of the combined shape and texture variation. The desire was to present a better case study with improved image quality and texture resolution before continuing efforts on labeling and modeling the entire MORPH database.

A forensic sketch artist was employed to render sketches to be compared to the synthetic images. Examples of the average age-progression as represented in the second

FIGURE 7 Average faces over age-progression with second setup, from 20 to 70.

study are shown in Figure 7. Figure 8 demonstrates the loss of visual information and model construction as fewer parameters are chosen. The second setup uses 99 images but relatively few people, five individuals, to build a model, but it is in a sense a “family face space” that should and was proven to perform a reasonable representation of an individual and aging based on a wide representation of family images. It also represents one of the widest age ranges attempted so far, from approximately 20 to 70.

Age progressions generated with this setup and technique are shown in Figure 9. Similar experiments were likewise conducted in de-aging the family members, as shown in Figure 10. Also shown here is the difference image between the reconstructed AAM image of the individual at age 50 and the AAM image age regressed to 30. Although it may be difficult perceptually to notice changes depending upon presentation, and changes may be mild, the difference image demonstrates changes in both shape and texture and in probable regions as discussed henceforth. Parallels may be drawn about the regions in the face where rhytids, ptosis, loss of elasticity, and atrophy occur. Differences around the outer edge of shape may correspond to suggested small changes in the face length and shape due to skeletal remodeling as well [3]. The difference image presented in Figure 11 demonstrates changes from 34 to 70 in an individual. Regions of change include the center forehead where documented rhytids and ptosis occur. Just inside of the orbital regions, changes are indicated, such as are present in the glabellar rhytidosis that occurs there. Regions above, below, and around the eyes also indicate change represented by the aging model that correspond to the areas where lid ptosis and rhytidosis and lateral canthal rhytidosis occur. In Figure 12, the lower region, similar comparisons may be made. Change is evident in the nasolabial regions that typically develop creases in older age; change is also apparent in the lip regions where thinning and atrophy often occurs; and some change is evident in the chin region where ptosis and retraction occurs [3, 4].

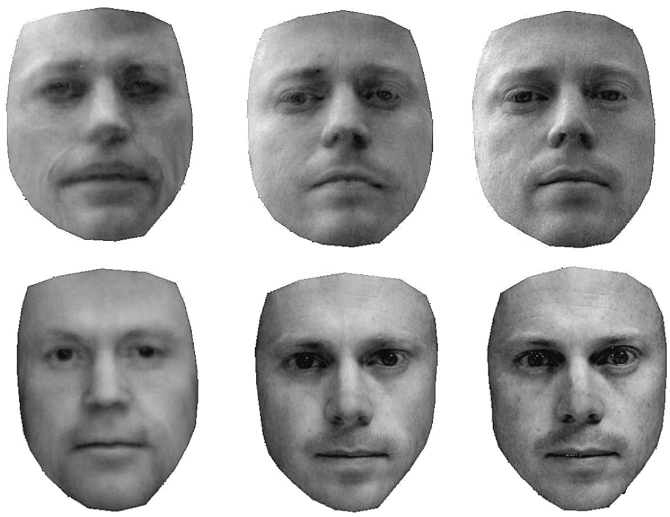

FIGURE 8 Parameter variation with 10, 30, and 50 parameters.

FIGURE 9 Different images of an individual synthetically progressed from ages 23, 25, and 34 (top to bottom) to 40, 50, 60, and 70 (left to right).

3 RESEARCH DIRECTIONS

The temporal results of FRVT 2000 show that recognizing faces from images taken more than a year apart remains an active area of research. Given the inadequacy of the existing databases, emphasis should be laid on significant data collection—both in breadth and

FIGURE 10 De-aging example from 50 to 30. Top images include original reconstruction, de-aged image, and difference image of reconstructed and de-aged. Bottom images are original and composite.

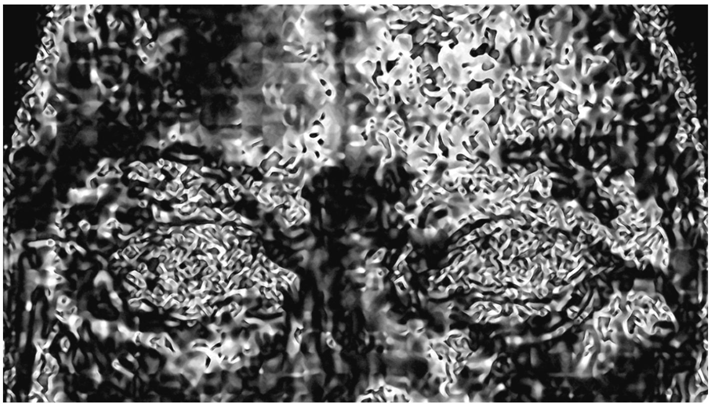

FIGURE 11 Aging effects, upper facial region, as demonstrated by difference of progression.

depth of individuals which is the approach being sought by the developers of MORPH [33] and the collection work by Notre Dame's Kevin Bowyer and Patrick Flynn.

Some previous work in the area of growth and development centered on the deformations of bony changes as modeled with cardioidal strain maps, [43, 44] are arising for the study and modeling of adult age-progression. Cardioidal strain transformations can be described as geometric transformations of the face. Although this approach has been predominately used to model cranioskeletal changes of the face due to growth and development, researchers are applying this method to soft tissue (texture) deformation [7].

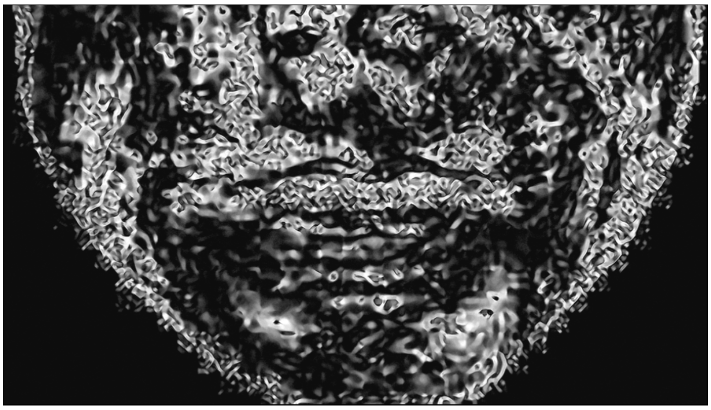

FIGURE 12 Aging effects, lower region, as demonstrated by difference of progression.

Q8 Fundamentally, the objective is to create FR systems that are resilient to adult age-progression by exploiting a feature space that is invariant over time; however, there has been a paucity of work in this area. Therefore, work in developing aggregate systems as in synthetic templates must continue. To this end, research should be directed toward quantifying the performance of FR systems on existing databases, generating metrics to judge synthesized age-progressed likeness, investigating and authenticating various aging techniques, and modeling age-progression with more input from metadata. From this work, a deeper understanding of aging will drive the development of age-robust FR systems.

To encourage more work in this critical area, more attention should be directed to this problem via workshops, symposia, and grand challenges. Finally, more funding should be made available in this active area of research (US and European Union funding of this problem has dwindled whereas corporate research dollars are on the rise in many Asian countries).

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Queries in Chapter 267

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