Improvements in Active Appearance Model Based Synthetic Age Progression for Adult Aging

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***Abstract*— Normal adult aging in the face can drastically affect performance of face recognition systems. Synthetically generating age-progressed or age-regressed images for aiding recognizers is one method of improving the robustness of face-based biometrics. These synthetic age progressions may also aid human law enforcement and other applications. There has been wide interest in these techniques in recent years, and the use of Active Appearance Models (AAMs) for synthetic age progression has been shown to be a promising approach but has not yet been demonstrated on a large human population with wide variation. This paper presents improvements in AAM-based age progression that generate significantly improved visual results, taking into account a much wider gender, age, and ethnic range than published to date for age progression techniques.**

I. INTRODUCTION

The human face undergoes significant variations in shape and texture due to the normal aging process. Morphology is affected by many factors such as gender, ethnicity, solar exposure, smoking, drinking, and weight loss or gain. Development of face-based biometric algorithms that are invariant to these temporal changes is highly desirable for applications in law enforcement, forensics, medicine, and other fields. Recently, as face recognition technologies have improved, it has become important to look at more difficult, "real-world" challenges such as how the face changes throughout lifetime. A span of even a few years may significantly degrade recognition performance.

In this work, we consider adult aging – a separate process from growth and development which has been demonstrated to some success in AAM-based systems. In the formative years, pre-adult processes cause largely shape-based changes in the mid and lower face. Adult aging, however, occurring after roughly twenty years of age, consists of shape deformation from weight change, minor bone remodeling, and tissue degeneration. Adult aging is also affected by gravity effects and significant textural changes due to a variety of complex phenomenon [1]. One of the best approaches demonstrated thus far for synthesizing these changes in images of the face is the use of Active Appearance Models (AAM) for a feature space that takes into account aging variation. In this paper we discuss recent developments in AAM-based synthetic adult age progression and present recent, high-quality images generated using these techniques that were not possible before and compare very favorably with any images published thus far. Our goal is to create synthetically age-progressed images that portray actual effects that occurring in humans as documented in medical and anthropological literature, and to do this over a wide variation of human population.

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Here, we present a brief review of literature concerning aging of the human face then discuss recent work we have conducted in synthetic age progression, presenting several resultant images. (As no clear quantitative metrics have been presented to date, visual comparison is one of the few ways to rate synthetically generated age-progressed images). Lastly, we present some concluding remarks with a brief discussion of ongoing research in the area.

II. RELATED WORK IN FACE AGING

A few computational approaches have been considered concerning simulation of aging in facial images. They can be broadly divided into geometric or physical based [2] [3] and analysis-synthesis model-based methods [2] [4] [5]. In general, computational methods take a two-step approach towards facial aging, involving estimating the current age of the face in an image and then generating parameters to modify the image to appear age-progressed by a certain amount of years. Tiddeman et. al [6] used wavelets to model wrinkles on age-based face composites. Ramanathan et. al [2] characterised age-based appearance variations using subspace methods and in [3], they proposed a two-fold approach towards modeling facial aging in adults. Park et. al [7] propose an automatic aging simulation technique by using a 3D morphable model. However, some of the most promising analysis-synthesis methods have involved a variation of active appearance models (AAM) [8], [9] for growth and development [10], [11] or adult aging [12][13]. In [14], Ramanathan, et al. present a more thorough survey of some of the techniques, although they do not go in much depth on the results generated via AAM-based methods.

III. DEVELOPMENTS IN SYNTHETIC AGE PROGRESSION

Recent improvements made in synthetic age progression of images of adults are discussed in this section. Our objective is to produce accurate estimates of the changes that occur in the appearance of the individual due to the effects of aging. Ultimately, techniques that can account for individualized aging would be most accurate. Development of accurate models of individualized, idiosyncratic aging models, however, requires a large set of representative longitudinal data for the same individual across adult lifespan. Since such data is not generally available, most work is still focused

Fig. 1. First few modes of the Active Appearance Model (representing variation along the mode axis from left to right, with the mean appearance face in the center) trained on 541 images representative of adult aging, demonstrating represention of age, gender, and ethnic variation.

on "general" models of aging, and many of these have been data starved. For recent developments, we have focused our work in age-progression on improving landmarks, use of AAM parameters, methods for training aging models, and improving general quality and quantity of data.

Fig. 2. Images from earlier work included for comparison, one of the authors age-progressed through the major decades. The top two rows are earlier versions (at original age 30 then 40,50,60,70), the bottom row aged using the recent model (synthetic from 20 to 80 at the decades).

Several images from Face and Gesture Recognition Research Network (FG-NET), one of the few databases available for comparison with its age-spaced samples of the same individuals, were synthetically aged with good result; two commonly chosen faces are shown in Figure 3. For comparison, the original images are shown in the first row and the synthetic aged images are shown in second and third rows. Figure 4 shows synthetic age progressed images for an individual at various ages compared to original images at approximately the same ages in the row above. In addition, images of celebrities were obtained and synthetically aged as shown in Figures 5 - Figures 9.

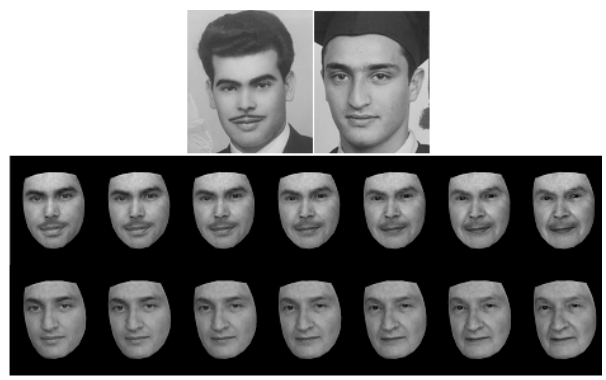

Fig. 3. Original samples of FG-Net shown in first row. Bottom two rows are aged through the decades 20 to 80 years.

A. Methodology

Active Appearance Models (AAM), a group of flexible deformable models, have been successfully used for face and gesture recognition in recent years because of their great capability for representing high-level information about images such as those of faces. Our work uses an analysis-synthesis face-model approach, using AAMs as the method of representation for both shape and texture information. The procedure follows:

1) Annotate representative images with age-related landmarks over the face [12], [13].
2) Build an AAM model using these, generating parameters for all faces that will be used to build age model.
3) Use support-vector regression (SVR) to learn age-related properties of AAM parameters across the entire

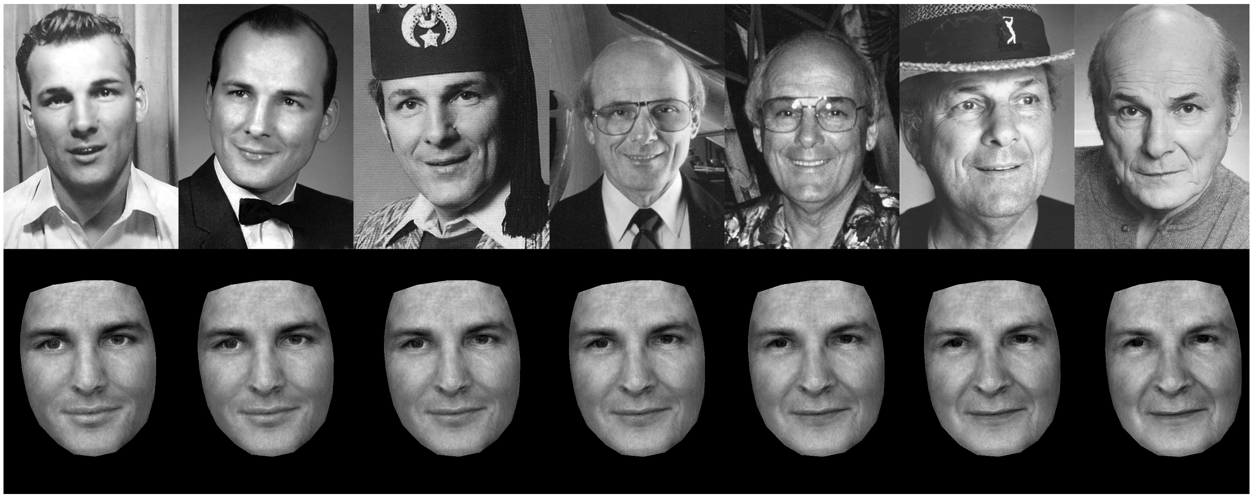

Fig. 4. The first row shows original images of an individual. Bottom row shows synthetic aged images at approx. same ages as the images above.

training set, training parameters against age value.

4) Generate feasible random faces over 500,000 iterations using Monte-Carlo simulation; classify each using age-estimation "learned" by the support-vector regression.
5) Lastly, generate a table of representative age parameters, where each year is a bin represented by the average at that year created by the simulation. This table is used to index and difference AAM parameters to age-progress or regress the parameters in the feature space for synthesizing a new image that should appear older or younger by the chosen span.

This methodology presents several changes from previous work published in this area, including our own. We recently switched to gradient-regression-based AAMs due to work by Cootes that suggested that these may best represent texture information in faces [15]. Secondly, we switched from using an "aging" equation and genetic algorithm for learning age parameters such as presented in [11] and [12] to the use of support-vector regression (SVR) for learning aspects of the movement of parameters in AAM space related to aging. Thirdly, we increased the number of iterations in the Monte-Carlo simulations and improved the method of generating feasible faces to build the common age table.

Along with this, we used more images than used thus far in AAM or age-progression systems, including a total of 541 images (neutral images selected from the PAL Database) for training the AAM, pushing the memory and computational limits of the AAM implementation being used. While doing this, we manually labeled the images with a high degree of accuracy to ensure quality results. Lastly, our image set included a wider range of ethnicity and gender than used so far in age-progression studies. The end result of these improvements are evident in some of the principal modes of the AAM used to build the age-progression system as shown in Figure 1.

All age-progressed images in this paper are also not present in the AAM-model nor aging model training data and are completely re-synthesized as well as age-progressed and synthesized without prior knowledge trained into the models. Texture-quality could possibly be improved by including them in the AAM, thus allowing for better "reconstruction," but it demonstrates the representation capability of the current AAM to re-synthesize all of these images to a high quality with no prior AAM training knowledge of the faces. (Some comprehensive AAM and 3DMM results published are visually skewed toward whatever particular element of the population was used for training). Figure 2 demonstrates improvements in an age-progression of one of the authors compared to earlier published work [13].

For purposes of testing our model, we age-progressed numerous images from the most notable longitudinal databases FG-NET [16] and MORPH [17]. Currently, FG-NET [16] and MORPH [3] are the two main publicly available face-image databases that attempt to represent longitudinal changes. Celebrity images were also used to test the model, as these are common, and some other age-progression work has presented similar images. Our desire was to demonstrate images that could be compared directly with other works since no common metrics are employed thus far.

The results presented here for a wide variety of images show considerable improvement in modeling shape and texture as well as better demonstrate expected age-related changes. These correspond well to the aging process documented in the anthropological and medical literature. Some of these age-related changes that are well-modeled are the depth of the nasial-labial line, the rhytids below the lips, general sagging across the face and under the eyes, as well as general textural changes. Although it may be difficult to compare quantitatively to other work, we believe that these images compare very favorably and represent some of the highest quality synthetically age-progressed images published to date.

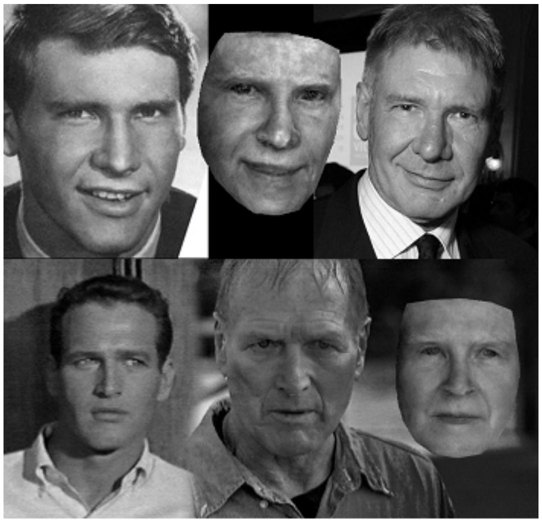

Fig. 5. Top: Original image of Harrison Ford (left) aged to about 65 years. Synthetic image is shown in the center and the actual image at 65 is on the right. Bottom (L-R): Original image of Paul Newman at approx 33 years; Original image at approx 75 years; synthetic aged image at age 75.

Fig. 6. Top: Original image of Bette Davis at age 30 (left); reconstructed image at age 30; synthetic-aged image at age 70; original Image at age 70(right). Bottom: Image synthetically aged to age 80 (right) compared to original images at 30 and 80 years (left).

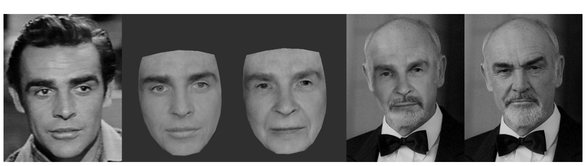

Fig. 7. From L-R: Original image of Sean Connery at approx age 30; reconstructed image at age 30; synthetic aged image at age 80; synthetic aged image with head and facial hair; original Image at age 80.

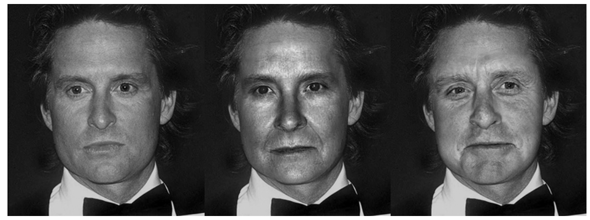

Fig. 8. Top:Synthetic Age Progression of Michael Douglas from age 20 to age 80. Bottom: From L-R: original image of Michael Douglas at approx age 40; synthetic aged image at age 65; original Image at age 65.

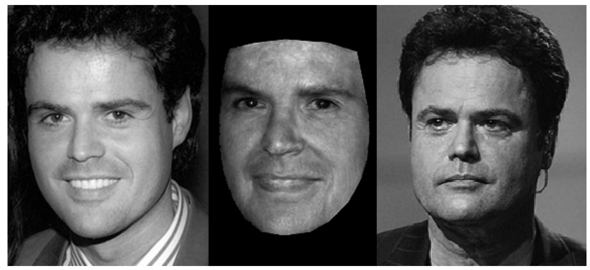

Fig. 9. Top: Synthetic Age Progression of Donnie Osmond from age 20 to age 80. Bottom(L-R): original image at age 40; synthetic-aged image at age 50; original image at age 50.

B. *Age-Progression Application Development*

In addition to improvements in AAM-based, technique, we present an age-progression application that we developed. Two user interfaces were created for the purpose of manipulating images for use of our AAM algorithms. These were developed using Matlab as well as the Image-Processing Toolbox. The first interface was developed to rapidly annotate facial images with a standardized set of 161 marker points. The annotated points can then be saved into .pts files for use in the applications using AAMs. Using this tool, points are aligned to features on the face one is trying to annotate as shown in Figure 10.

The second interface was created for a minimally trained individual to be able to synthetically age-progress any face image. It is used to load facial images, annotate them with the standard 161 points, save the annotation in a .pts file, develop AAM parameters, estimate the age of the person in the image, artifically age (or de-age) the person in the image, and display the appearance of the person at that desired age. Figure 11 displays the interface after the process. At the top left is the original image. At the bottom left is that image annotated with 161 points.At the bottom right is the reconstructed image using the AAM model. At the top right is the reconstructed image redisplayed. Next to this image is a slide bar where the age of the reconstructed image can be changed. When the age is changed, the image is reconstructed at the new age.

IV. Conclusions and Suggested Direction

In this paper, we have presented recent work and results in AAM-based age progression. The improved methods gener-

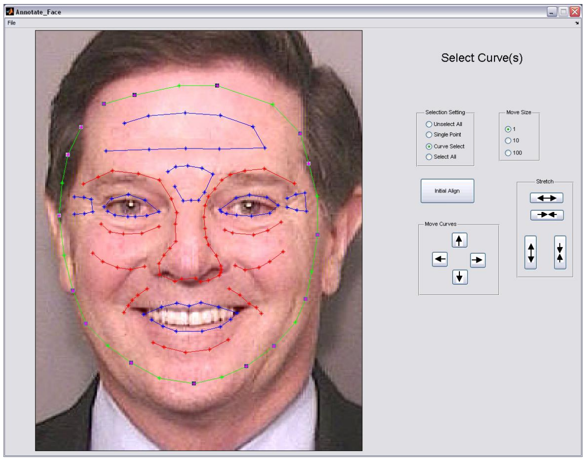

Fig. 10. Matlab tool to annotate face.

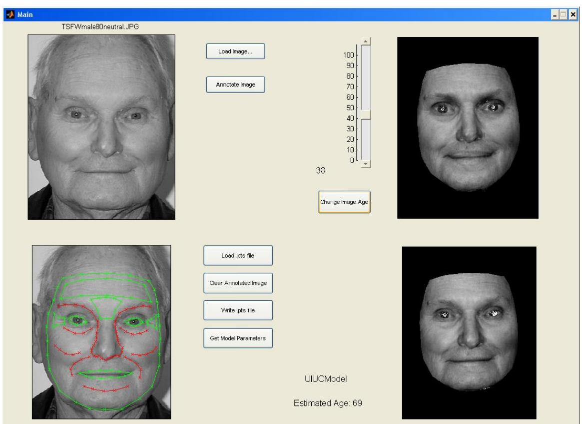

Fig. 11. Matlab tool for the main Interface.

ate images that are cleaner, higher-resolution, and in general, better represent the expected changes with aging in adults. The AAM-based model and age-models illustrated also better represent gender and ethnicity variation; this is one area that we are currently focusing as well, building ethnic-based and gender-based models of aging for comparison. AAM-based synthetic age-progression has been presented before, but results published thus far have not yielded quality images. These results, however, present much higher quality images which are realistic and accurately model at least general age-related changes. These images also compare very well with recently published results and are perhaps some of the most realistic generated over a wide range to date. We are currently developing color AAM-models for testing; an initial color average age model is demonstrated in Figure 12. We are also working toward classifiers and systems for individualized age-progression as previously mentioned. As this is a new area of study, there is still much room for the development and collection of higher quality longitudinal data as well as continued refinements, even in known techniques, for

Fig. 12. Average face images for decades 20 to 80 from a color aging model in progress.

improved overall results. AAM-based methods, and their three-dimensional equivalents, 3-D Morphable Models, have been demonstrated to work quite well in a variety of areas, but further depth and refinement with continued efforts are still needed.

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