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# Aging Simulation by Patch-based Texture Synthesis with Statistical Wrinkle Aging Pattern Model

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We propose a method for synthesizing a photorealistic human aged-face image. Our method is based on the patch-based texture synthesis using a set of human face images of a target age. The advantage of our method is that it synthesizes an aged-face image with detailed skin texture such as spots and somberness of facial skin, as well as age-related facial wrinkles without blurs that are derived from lack of accurate pixel-wise alignments as in the linear combination model, while maintaining the quality of the original image.

## 1. Introduction

Predicting the current facial appearance of wanted or missing people who have been missing for several years is an important task in criminal investigation. Previously, sketches or photomontages have been used for this purpose. However, it is not easy to predict and depict one's realistic facial appearance only from photographs that are several years old and some interviews, because the quality of the resulting sketch or montage highly depends on the skill of the forensic artists. Thus, an automatic facial aging simulator, which can synthesize a photorealistic facial appearance based on statistics from the actual aging process, is required.

Automatic facial aging simulation has been considered by many researchers [1, 2, 7, 4, 6, 9]. Most of the conventional methods used for facial aging simulation adopts a linear combination model such as active appearance model [2, 1, 4, 6] or 3D morphable model [7] to parameterize facial geometry and appearance. However, in the case of linear combination, which relies on bases, the resulting image is somewhat blurred because the alignment between features, which appear for different individuals or ages is impossible. Thus, it is difficult to represent subtle features such as spots and somberness of facial skin. To solve this problem, Tazoe et al. have proposed patch-based facial aging texture synthesis using human face images of the target age [9]. This method is based on the assumption that if we accurately reconstruct an input face using image patches of the target age, the resulting face would be the same individual's aged-face. Actually, their method can generate a photorealistic face image with subtle age-related features. However, the resulting face sometimes does not look like the original person because the original face has been completely replaced by the reconstructed face.

Moreover, age-related features such as wrinkles may be expressed depending on the pixel intensity pattern of a patch in the input image.

In this paper, we propose an automatic facial aging simulation, which can overcome the above mentioned problems. Our method is based on patch-based texture synthesis using facial images of the target age. Using the statistical wrinkle aging pattern model, we predict the resulting facial wrinkle appearance (shape, depth, and length) of the target age. Moreover, we introduce a modified Poisson solver to seamlessly merge between image patches, and to keep the original facial appearance in the region which influences the individual recognition and skin tone. The principal contribution of this paper is to provide a simulator, which can synthesize photorealistic aged-face images with detailed textures such as spots and somberness of facial skin, as well as age-related facial wrinkles, while maintaining the identity of the original face.

## 2. Patch-based Texture Synthesis Using Age-specific Patches

Given an input face image and target age, patch-based texture synthesis using age-specific patches is performed by the following procedures.

**Preprocessing:** We collect face images corresponding to various ages, and create an average shaped face model, and shape normalized face images by the same procedure of runtime processing (a) (c). Then, we divide shape normalized face images into small patches. At the same time, indexes representing the original position before cutting out are labeled to each patch. Then, we construct patch databases for which patches are grouped according to the labeled index.

**Runtime processing:**
(a) Facial feature points are detected from the input image using Zhang's technique [10].
(b) The average face model is deformed using radial basis functions [3] so that the vertices of the face model are matched to corresponding detected feature points.
(c) The deformed face model with the input image is rendered into the image. As a result, we can obtain a face image that the shape is normalized to the average face.
(d) To simulate individual aging, especially with facial wrinkle, which significantly influence cognition, pseudo facial wrinkles (actually line drawings) are overwritten onto the shape normalized image according to the statistical wrinkle aging pattern model (details are described in the next section).
(e) The shape normalized face image is reconstructed by patch-based texture synthesis using patches of the target age. The patch-based texture synthesis can be done by selecting patches with a minimum energy $E$ at each labeled index $(i, j)$ from the patch database and tiling selected patches. The energy function $E$ is defined by equation (1).

$$E(i, j, n) = \alpha * E_g(i, j, n) + (1 - \alpha) * E_l(i, j, n) \tag{1}$$

where $n$ represents an unknown patch id, which we would like to find at index $(i, j)$, $E_g$ is the fitness, which is defined as a distance between a normalized face image and patches at index $(i,j)$. $\Omega_{i,j}$ represents the region of an indexed patch at $(i,j)$, $\mathbf{I}$ means a feature vector (for example, RGB color vector at pixel $(x,y)$) of a normalized face image and $\mathbf{P}$ is that of a age-specific patch,

$$E_g(i,j,n) = \sum_{x,y\in\Omega_{i,j}} ||\mathbf{I}(x,y) - \mathbf{P}^n_{i,j}(x,y)||^2 \tag{2}$$

$E_l$ is a regularization term, which preserves the spatial coherency between the selected patch and its neighboring patches. Obviously, $E_l$ is calculated by the sum of the Euclid distance between feature vectors that both overlap regions between the selected patch and its neighbors. For each index $(i,j)$, optimal patches are selected by minimizing the energy function (1). Finally, the normalized face image is reconstructed by tiling selected patches along with the raster scan order.
(f) The modified Poisson solver [8] merges selected patches in the gradient domain. Assuming that $\mathbf{f}$ is the desired pixel intensity, $\mathbf{f}^*$ represents the corresponding intensity of the shape normalized face image, and $\mathbf{v}$ is the gradient. The modified Poisson problem can be represented by the following equation.

$$\min_f \left( \int_T ||\mathrm{div}\, \mathbf{v} - \Delta\mathbf{f}||_2^2 \, dt + \epsilon \int_T ||\mathbf{f}^* - \mathbf{f}||_2^2 \, dt \right) \tag{3}$$

where, $T$ is the region for the whole image, and $\epsilon$ is the weight, which decides the effect from an input image. If we set a small $\epsilon$, the resulting image would be affected by the color of the reconstructed face image. In this paper, we modify the original equation proposed by Tanaka et al. [8] to preserve the original skin tone of the input face as much as possible. By discretizing equation (5) and vanishing the derivation for a pixel value $f_p$ at a pixel $p$, we can obtain the following equation.

$$(\epsilon + |N_p|)f_p - |N_p| \sum_{q\in N_p} f_q = \epsilon f_p^* - |N_p| \sum_{q\in N_p} v_{pq} \tag{4}$$

where $f_p$ is the pixel intensity at a pixel $p$ and $\epsilon$ is the weight, which decides the effect from an input image. If we set a small $\epsilon$, the resulting image would be affected by the color of the reconstructed face image. $N_p$ is a set of neighboring pixels at pixel $p$, and $|N_p|$ is the number of neighbors. Also, $v_{pq}$ is defined by the following equations.

$$v_{pq} = \begin{cases} g_p - g_q & if\ p \in \Omega \\ f_p^* - f_q^* & otherwise \end{cases} \tag{5}$$

where, $g_p$ and $g_q$ represent the gradients of the reconstructed face image, $\Omega$ also represents the region in which the gradients can be transferred (age-related characteristics can be reflected). We define the region $\Omega$ which contains the eyes, nose, and lips to retain the identity of the original face. We consider equation (5) for all pixels in the entire image and solve a sparse linear system. Finally, we can obtain the pixel intensity $f$ for each pixel.
(g) The shape of the resulting face is deformed toward that of the original face by

performing an inverse operation of (3). The complete aged-face image is generated by embedding the resulting face into the input face image.

## 3. Modulating Patch Selection Result with Statistical Wrinkle Aging Pattern Model

In the texture synthesis phase, the occurrence and properties such as shape, depth and length, and the number of wrinkles depends entirely on the pixel intensity pattern in the focusing patch. To simulate facial wrinkle aging, we introduce a Statistical Wrinkle Aging Pattern Model (SWAPM) that can implicitly predict the wrinkle appearance, including shape, depth, and length. The SWAPM provides a cue where the appropriate patch can be selected in the patch selection process. The SWAPM can be constructed by carrying out the following procedures using a longitudinal facial image database such as the MORPH database [5].

(a) Manually marking on left-right laugh lines, left-right crow's feet, and facial wrinkles on left-right orbits and forehead for each image in the database.
(b) Approximating each marked line using a parametric curve and parameterizing each wrinkle by acquired parameters and wrinkle density of each facial wrinkle. More specifically, we use a Ferguson curve for this approximation. The position and velocity at the start/end points of the approximated curve and depth that are decided based on the intensity distribution around the approximated curve are stacked into a vector form for all approximated curves. We refer to the resulting vector as the wrinkle vector for an individual.
(c) Collecting all wrinkle vectors at existing ages in the database and train the aging pattern model in the same manner as the work by Park et al [4] using principal component analysis. We refer to the resulting linear combination model as the SWAPM.

By changing the coefficient of the SWAPM, we can change the shape, depth, and length of the wrinkles of the model, and can modulate the patch selection result by adding or subtracting the pixel intensity from resulting wrinkles to a shape normalized image. We demonstrate aging simulation results with or without SWAPM for an individual in Figure 1. We found that our model can describe the aging process of wrinkles implicitly, thus our simulation framework can utilize a longitudinal facial aging database, which contains facial images with a large variance in resolution and illumination change.

## 4. Result and Discussion

Simulation results are shown in Figure 2. We found that our method can represent subtle spots and somberness of facial skin that it are difficult to represent using previous methods, as well as age-related facial wrinkles. On the other hand, original features such as moles are missing or placed in other locations. This is because the gradients of the original image have been completely replaced by those of patches, which consist

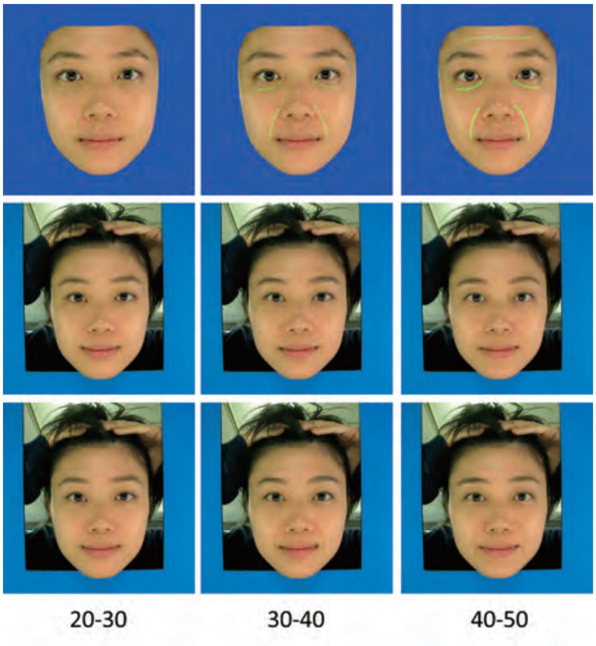


FIGURE 1. Changing patch selection results with SWAPM. The first row depicts simulated wrinkles on normalized face images at 20 - 30, 30 - 40, and 40 - 50 years old. The second row represents face reconstruction results without SWAPM.

from others except for the eyes, nose, and mouth region. However, this problem is easy to solve if some user interaction is allowed. Obviously, we manually mark the region in which we would like to retain the identity as $\Omega$ in equation (5). The capability to represent other aging effects including increasing/decreasing weights and changes in one's hair is one of the major concerns to be addressed in future work. Moreover, we plan to improve our face texture synthesis for large pose and illumination changes between an input image and patches, and to evaluate the performance of our method on public facial databases by performing a comparison with conventional methods.

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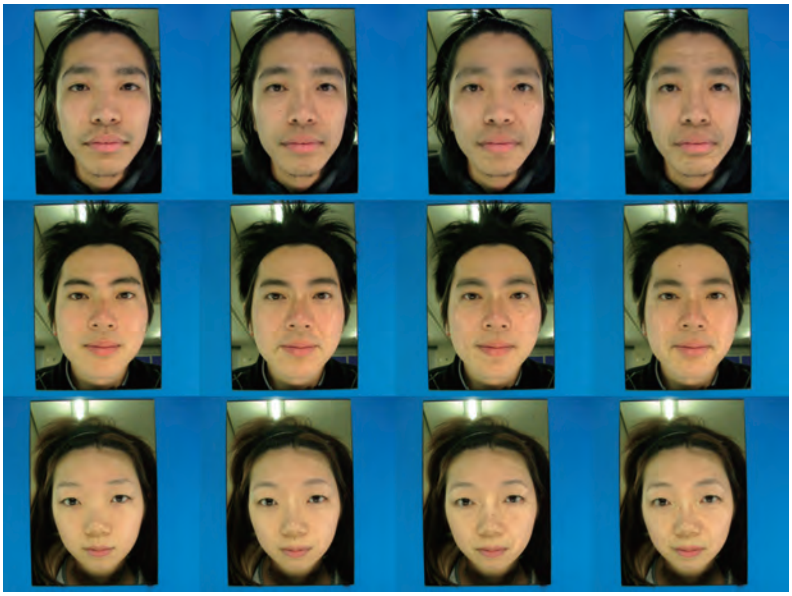

Figure 2. Results of simulation. From left to right: original image, synthetic images for ages 40, 50, and 60 for each subject.

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