Facial Skin Beautification Using Adaptive Region-Aware Masks

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***Abstract*—In this paper, we propose a unified facial beautification framework with respect to skin homogeneity, lighting, and color. A novel region-aware mask is constructed for skin manipulation, which can automatically select the edited regions with great precision. Inspired by the state-of-the-art edit propagation techniques, we present an adaptive edge-preserving energy minimization model with a spatially variant parameter and a high-dimensional guided feature space for mask generation. Using region-aware masks, our method facilitates more flexible and accurate facial skin enhancement while the complex manipulations are simplified considerably. In our beautification framework, a portrait is decomposed into smoothness, lighting, and color layers by an edge-preserving operator. Next, facial landmarks and significant features are extracted as input constraints for mask generation. After three region-aware masks have been obtained, a user can perform facial beautification simply by adjusting the skin parameters. Furthermore, the combinations of parameters can be optimized automatically, depending on the data priors and psychological knowledge. We performed both qualitative and quantitative evaluation for our method using faces with different genders, races, ages, poses, and backgrounds from various databases. The experimental results demonstrate that our technique is superior to previous methods and comparable to commercial systems, for example, PicTreat, Portrait+, and Portraiture.**

***Index Terms*—Edge-preserving smoothing, edit propagation, face beautification, facial attractiveness, image editing, region-aware mask.**

I. Introduction

PEOPLE have always sought out beauty and countless philosophers, artists, and scientists have tried to capture the nature of beauty. Facial attractiveness has been studied extensively as an important part of aesthetics, and recent psychology research has shown that the perception of beauty is consistent among individuals, regardless of their gender, ethnicity, or age [13], [14]. A universal definition of beauty remains elusive, but the consistent perception of facial attractiveness indicates that machine-based analysis of facial beauty and facial beautification will probably have many useful applications, as well as roles in research.

The phrase *face beautification* comes from a recent study by Leyvand *et al.* [1], which presented a novel computational photography technique to enhance the aesthetic appeal of human face images while maintaining high similarity with the original image [1], [34].

Face beautification is a widely used technique. Advertisements, magazines, and websites manipulate numerous facial image everyday. Some commercial image-editing software systems are available (such as Adobe Photoshop) but face image retouching is still a time-consuming task. Furthermore, image enhancement and image sharing are becoming more prevalent as social networks (e.g., Facebook, LinkedIn, and Flickr) become increasingly popular. Most users require immediate facial beautification with the minimum number of operations to avoid tedious manipulations. Thus, it would be useful to develop a face image beatification technique that is effective, convenient, and flexible.

The increasing demand for face image retouching has led to many studies, such as facial geometric beautification [34], digital facial makeup [29], personal photo enhancement [20], and hair modeling [21]. In this paper, we focus specifically on facial skin beautification [24]–[26], which is one of the most important and time-consuming tasks during face image editing. When facial skin is manipulated, the edited regions should be selected accurately by a facial mask to avoid visual artifacts. It is possible to draw (or paint) a mask manually, but this involves many complex operations. Therefore, it is necessary to simplify the task of mask generation during facial skin beautification.

According to recent research, there are two ways of obtaining a facial mask. The first method regards facial mask generation as a specific image segmentation problem, which involves integrating the facial priors (such as the skin color or shape) into a segmentation model [24]–[26]. This approach avoids the tedious task of mask painting, but the mask boundaries often fail to follow the region boundaries closely, which may introduce visual artifacts.

Another method for improving mask generation is to construct a much simpler and more intuitive interactive

Manuscript received September 23, 2013; revised March 3, 2014; accepted March 4, 2014. Date of publication April 1, 2014; date of current version November 13, 2014. This work was supported in part by the National Science Foundation of China under Grant 61125106, Grant 61075021, and Grant 61201348, in part by the National Science and Technology Support Plan under Grant 2013BAH65F01 and Grant 2013BAH65F04, in part by the GDSTP under Grant 2012A010701001 and Grant S2012040008016, in part by the Research Fund for the Doctoral Program of Higher Education of China under Grant 20120172110023, and in part by the Shaanxi Key Innovation Team of Science and Technology under Grant 2012KCT-04. This paper was recommended by Associate Editor Q. Zhao.

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Digital Object Identifier 10.1109/TCYB.2014.2311033

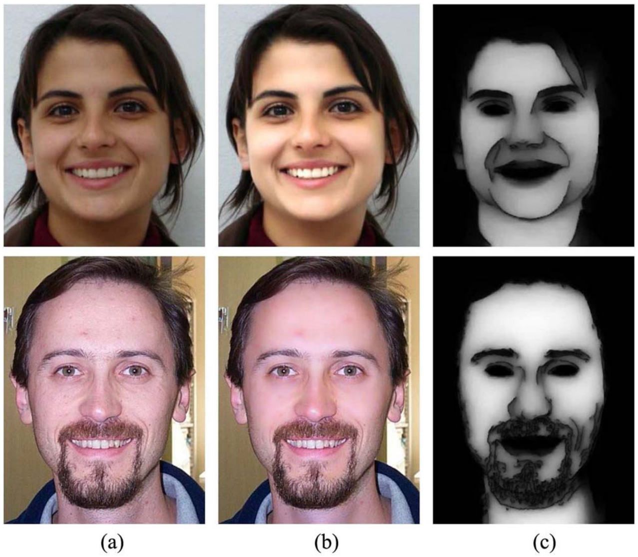

Fig. 1. Automatic facial skin beautification using region-aware masks. The original images were taken from FEI [19] (top) and Caltech [18] (bottom) face database. The results illustrate that our method could effectively beautify faces and well preserve the identity and significant details of portraits. (a) Original. (b) Beautified. (c) Region-aware mask.

manipulation tool. An edit propagation technique has been proposed [3], [50]–[52] to achieve this goal, which propagates sparse user edits throughout the entire image according to the pixel affinity [52]. A significant advantage of edit propagation is its edge-aware property, which produces adaptive transitions between the boundaries of different regions without any user intervention. Therefore, this method has been applied widely to many image-editing problems, such as colorization [50], high-dynamic range [51], image matting [52], and tonal adjustment [3]. During facial skin beautification, various regions need to have different edge-aware levels, depending on their editing properties. However, existing edit propagation methods based on homogeneous parameters may fail to produce specific variable diffusion effects for facial masks, while interactive initialization appears to be cumbersome for beautification tasks.

To overcome the shortcomings of these methods, we propose an automatic region-aware mask-generation method for facial skin beautification, which is based on the edge-preserving energy minimization framework introduced by Lischinski *et al.* [5]. The original model employs sparse user scribbles as input constraints and propagates the values of the inputs to other regions, according to the gradient property of a guided image [5]. To simplify this process further, we replace the user scribbles with rough regions, which are selected by face feature detectors. To perform adaptive edit propagation, we extend the original model in two aspects. First, we generalize the guided image to a guided feature space, which means richer feature information [10], [12], [59] or more sophisticated similarity measurements [2]–[4], [56] can be used to guide the propagation. Second, we adopt a spatially variant model parameter instead of a homogeneous parameter [53], so that better edge-preserving effect could be obtained in the region boundaries. Our method eliminates most of the user interventions and produces a region-aware mask that fits the boundaries of different facial components and features in an appropriate manner.

Thus, we propose a unified facial skin beautification framework based on the adaptive region-aware method. According to psychology research, the skin homogeneity (smoothness), lighting, and color are three main attributes that affect the perception of facial attractiveness [44]–[46]. Our beautification framework encompasses all three skin properties, that is, smoothness, lighting, and color, and it provides two manipulation schemes: automatic and interactive. A portrait is decomposed into three layers with respect to each skin property using an edge-preserving smoothing filter [32]. Next, three region-aware facial masks are generated for specific layer manipulations. The masks allow users to control the beautification process in an effective manner simply by adjusting the skin parameters. Furthermore, combinations of human-like adjustment parameters can be optimized automatically based on data-driven and knowledge-driven perception principles derived from psychology studies. We make no claims that the beautified faces achieve absolute attractiveness enhancement, although most of the results could compete with manually crafted manipulations to some extent, as shown in Fig. 1.

In summary, the specific contributions of our paper include the following:

1) a region-aware mask-generation method based on face feature detection and adaptive edit propagation techniques;
2) a unified facial skin beautification framework, which includes specific operations related to the main attractiveness attributes of smoothness, lighting, and color;
3) an automatic parameter optimization approach that integrates facial data and psychology knowledge;
4) a graphic user interface (GUI) system that facilitates automatic and interactive facial skin beautification.

II. Related Work

In this section, we review recent facial beautification methods and the related techniques. In the context of facial beautification, we consider facial geometry beautification, facial attractiveness prediction, skin manipulation, and some commercial systems. We also review the related techniques, and categorize them as facial makeup, photo enhancement, face segmentation, and edit propagation.

A. Facial Beautification

Facial geometry is one of the important facial attributes that affects attractiveness and it has been studied widely. Blanz and Vetter [22], [23] attempted to generate attractive faces using 3-D morphable models. Eisenth *et al.* [33] predicted attractiveness using machine-learning methods, including the k-nearest neighbor algorithm and support vector regression. Leyvand *et al.* [34] beautified facial structures based on a similar attractiveness predictor. Fan *et al.* [36] proposed an attractiveness predictor using facial proportions. Zhang *et al.* [37] transformed face shapes into a geometric feature space to facilitate facial beautification. In our study,

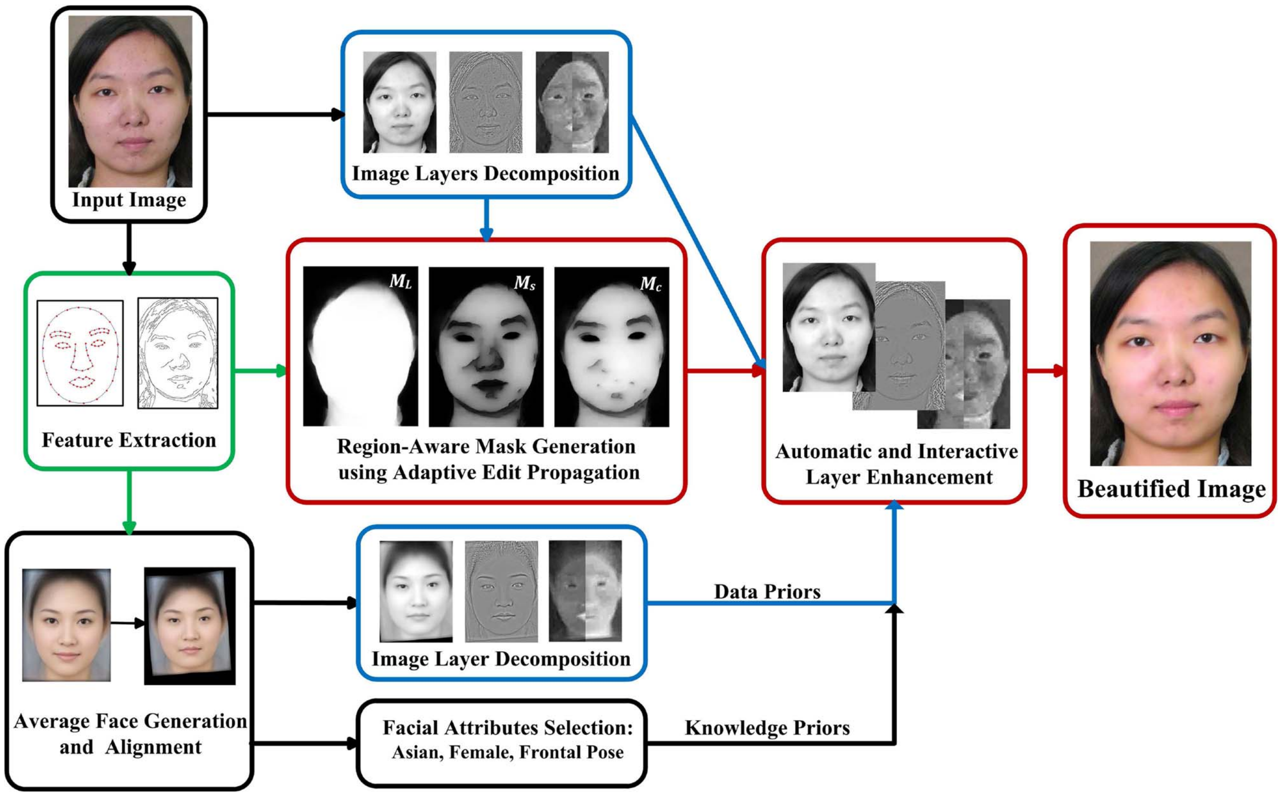

Fig. 2. Process of our facial skin beautification framework. Step 1: image layers decomposition using a edge-preserving smoothing filter. Step 2: facial landmarks and feature detection in facial components. Step 3: region-aware mask generation that is based on an adaptive edit propagation model. Step 4: specific skin layer enhancement that allows automatic parameter optimization and user customized adjustment.

however, we focus on facial skin beautification, which is complementary to the previous research.

The skin smoothness, lighting, and color are the three main attributes that influence facial attractiveness [44]–[46] and many studies have addressed these areas. Liu *et al.* [48] presented an integrated approach for portrait beautification, which comprised portrait division, portrait fusion, and color correction. Lee *et al.* [26] generated a skin segmentation map using a Gaussian mixture model (GMM) and Bayesian segmentation to allow automatic skin smoothness enhancement. Chen *et al.* [25] performed automatic skin color enhancement based on color temperature-insensitive skin color detection and edited faces using a bilateral filter with Poisson image cloning. Florea *et al.* [24] used skin detection and a Lee filter for high-definition video camera face enhancement. One of the main challenges of skin beautification is determining the edited regions and the adjustment values in an adaptive manner. In previous methods, however, the boundary of the mask fails to follow the boundary of the edited region closely, which may cause visual artifacts. To overcome this shortcoming, we generate a region-aware mask for skin manipulation using a state-of-the-art edit propagation technique, which has demonstrated its beneficial edge-aware property in many applications [3], [5], [50]–[52]. We provide a further discussion of edit propagation in the following sections.

Facial beautification has led to many interesting applications and commercial systems. PicTreat [15] is an online service and a smart phone app for photo retouching. Portrait+ [16] provides the user with different manipulation schemes for skin beautification. Portraiture [17] offers specific face retouching filters as an Adobe Photoshop plugin. Patents for skin and eye beautification [27], [28] have also been published in recent years. It is difficult to obtain all the technical details for these systems, but comparisons with representative systems such as PicTreat, Portrait+, and Portraiture were used to demonstrate the effectiveness and practicality of our method.

B. Facial Makeup and Photo Enhancement

Facial makeup is a closely related technique for facial skin beautification, because both the techniques are involved with skin editing. Scherbaum *et al.* [35] implemented a computer-based 3-D makeup-mapping program that used facial examples with and without professional makeup. Tong *et al.* [38] generated cosmetic makeup by transferring the appearance properties of a face with makeup onto a novel face image. Guo and Sim [29] decomposed input and example faces into detail, structure, and color layers, before digital makeup was implemented by blending the corresponding layers of the two faces. Our method shares a similar layer decomposition process with that proposed in [29], which uses a weighted least squares (WLS) edge-preserving operator [32]. However, we provide more flexible layer enhancement using region-aware masks, which are based on an edit propagation technique [5].

Since photo quality can probably affect the human perception of a portrait, personal photo enhancement is another technique related to facial skin beautification. Joshi *et al.* [20]

proposed a personal photos quality-improvement framework based on identity-specific examples, which comprised photo deblurring, lighting enhancement, and the super resolution of faces. Kang *et al.* [41] performed automatic personalized image editing using metric learning and active sensor selection techniques based on reference data sets. Bychkovsky *et al.* [42] tested different supervised machine-learning methods to predict the optimal parameter combination for global image tonal adjustments. However, image enhancement aims to improve the overall quality of images, whereas facial beautification is more concerned with facial-specific operations.

C. Face Segmentation and Edit Propagation

During facial beautification (or even general image editing), one of the key stages is to isolate the editing regions and determine the relative adjustment level between these regions. We could accomplish both tasks simultaneously using a layer mask. However, general mask painting is a time-consuming and tedious task. It is fascinating if we can produce the mask automatically, but mask generation is very challenging due to the high facial variances in the real-world condition.

One intuitive solution is to produce a mask using face segmentation methods. As the image segmentation is a very broad field in computer vision, we can only give a brief review for some specific skin segmentation methods. Huang *et al.* [61] constructed a challenging face segmentation data set from the labeled face in the wild (LFW) database, and they trained a standard conditional random field (CRF) model [58] to build a hair/skin/background labeler. Wang *et al.* [60] proposed a compositional exemplar-based model that regularizes the output of a segmentation using parts. Scheffler *et al.* [62] trained a labeler that combines color models, spacial prior, and a Markov random field model. Kae *et al.* [59] integrated the global shape prior into CRF to construct the GLOC (GLObal and LOCal) model for skin segmentation. However, directly using these model may introduce visual artifacts for skin beautification because (super)pixel-wise skin labeler produces mask with rigid boundary. Furthermore, the label information fails to control the adjustment values effectively.

To construct more powerful manipulation tools, edit propagation has been proposed in recent years and it has been applied widely to many image-editing problems [3], [50]–[52].

Our method is closely related to the tonal adjustment method of Lischiniski *et al.* [5], which employs the user's scribbles as input constraints and produces an adjustment map by minimizing a quadratic energy functional using a guided image. In our previous study, we use detected facial features as input constraints instead of the user's scribbles, which further simplifies the manipulation process [53]. In this paper, in order to obtain adaptive propagation effect, we generalize the idea of the guided image to a guided feature space, as proposed by Farbman *et al.* [3], and we extend the homogenous model parameter to a spatially variant function. Since more facial priors are considered to guide the propagation process, the adaptive region-aware mask can select the edited region with greater precision.

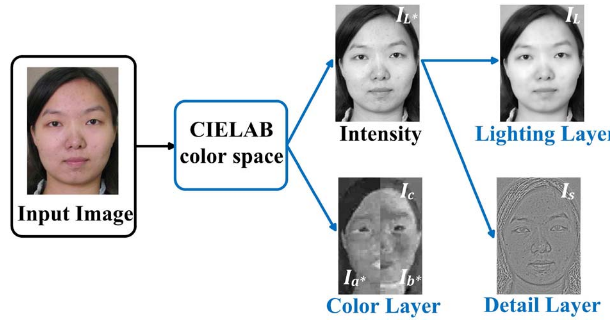

Fig. 3. Process to separate the input image into three specific facial layers using an edge-preserving smoothing filter [32].

III. Facial Skin Beautification Framework

Our facial skin beautification framework is illustrated in Fig. 2. There are two key components in the framework: region-aware mask generation and image layer enhancement. Region-aware mask generation produces a layer-specific piecewise-smooth mask for different skin enhancement operations. Image layer enhancement allows automatic manipulation using psychological priors and an average face template, as well as interactive manipulation with user-customized adjustments. The beautification process performed by our system is summarized as follows.

1) Decompose the image into lighting, detail, and color layers.
2) Locate the landmarks and extract the facial features.
3) Generate facial masks for the three layers.
4) Perform specific manipulations of the skin lighting, smoothness, and color.

Steps 1 and 2 are discussed in Section III, Step 3 in Section IV, and Step 4 in Section V.

A. Image Layer Decomposition

Our framework manipulates the skin lighting, smoothness, and color separately. A portrait is separated into three image layers according to the skin attributes, as shown in Fig. 3.

First, the input image I is converted into CIELAB color space, which has been used widely in human perceptual and facial attractiveness studies [45], [47]. The converted input image comprises a luminance channel L^* (I_{L^*}) and chromaticity channels a^* (I_{a^*}), b^* (I_{b^*}). The chromaticity channels are regarded as the color layer I_c. Second, we apply an edge-preserving smoothing operator to the luminance channel to capture its large-scale lighting variations, which is regarded as the lighting layer I_L. Finally, the lighting layer is subtracted from I_{L^*} and the residual is regarded as the detail layer I_s.

We use an edge-preserving smoothing operator based on a WLS framework [32] to separate the lighting and detail layers. The WLS filter is more suitable for detail manipulation than an explicit filter, such as a bilateral filter [39] or a guided filter [40], which would introduce halo artifacts [32], [40].

B. Feature Extraction

The goal of feature extraction is to locate significant facial regions, which are used as the constraints for mask generation. The important facial features include facial components (e.g., eyes, nose, and mouth), details (such as wrinkles caused by expressions), textures (e.g., beards and hair), and accessories (such as glasses). We could integrate all of these feature detectors into the framework, but such an implementation would not be an easy task. To simplify the analysis, therefore, we only consider representative features in this paper, including significant facial components and regions with meaningful facial attributes.

We use the Viola–Jones face detector [30] and the active shape model (ASM) [31] to locate the 86 landmarks in the facial components. In most cases, the process operates automatically, but minor user modifications may be required in some cases, for example, if the hair or pose obscure the face.

We also locate regions with meaningful facial details and textures as input constraints for mask generation. To avoid constructing a complicated feature detector, in the paper, we simply assume that significant edges in the face regions are caused by meaningful facial attributes (such as expressions, beards, or hair) and we employ a Canny operator [6] for edge detection in the lighting layer I_L, which contains large intensity variations. The edge extraction process is by no means optimal, but it works surprisingly well in most cases.

Note that more sophisticated facial feature extraction methods [7]–[10] could be integrated seamlessly into our current framework, which would probably produce better results, but this has been left for future research.

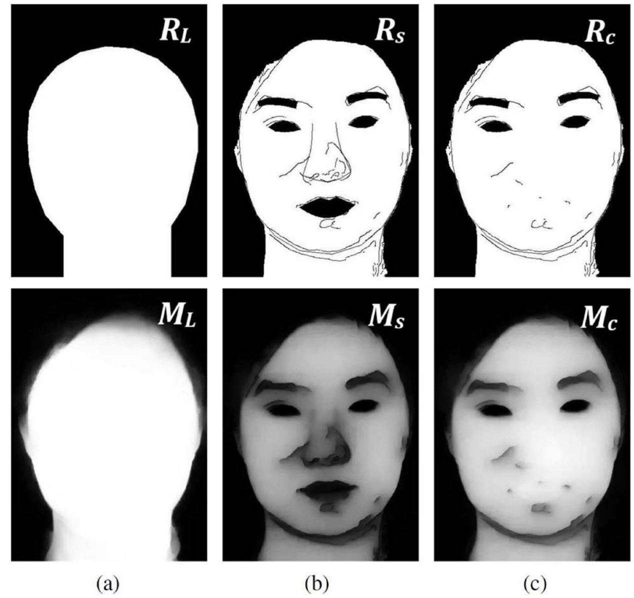

Fig. 4. Each column shows the input constraint (R_L, R_s, and R_c) and the output facial mask (M_L, M_s, and M_c) for lighting, smoothness, and color layer, respectively. In each mask, the intensity indicates the adjustment degree: the brighter regions would be under more manipulation whereas the darker regions would stayed unchanged. (a) Lighting layer. (b) Smoothness layer. (c) Color layer.

IV. Adaptive Region-Aware Mask Generation

During skin manipulation, we assume that a user wants to remove unwanted details (such as spots) or to adjust facial attributes (such as the skin color) in certain face image regions, while preserving unchanged information in other regions (such as the background). Thus, we isolate the edited region and control the degree of adjustment using specific layer masks for skin lighting, smoothness, and color enhancement.

To avoid tedious mask painting, we propose a region-aware mask-generation method using the adaptive edit propagation technique. In our method, the extracted facial features described in Section III-B are treated as input constraints. The pixel values of the constrained regions are propagated adaptively throughout the entire image according to the guided information and facial priors.

The implementation is based on an edge-preserving energy minimization model, which was originally proposed by Lischiniski *et al.* [5] for tonal adjustment. To ensure the clarity of presentation, we denote the spatial domain of an image as z, the input facial constraint as R, the output layer mask as M, and the guided information as G. We generate a mask by minimizing the following quadratic function:

$$M = \underset{M}{\operatorname{argmin}} \left\{ \sum_z w(z) \left(M(z) - R(z)\right)^2 + \sum_z h(\nabla M, \nabla G) \right\} \tag{1}$$

where

$$h(\nabla M, \nabla G) = \lambda \left(\frac{\|M_x\|^2}{\|G_x\|_p^{\alpha(z)} + \varepsilon} + \frac{\|M_y\|^2}{\|G_y\|_p^{\alpha(z)} + \varepsilon} \right). \tag{2}$$

The first term in (1) is the data term, which ensures that mask M satisfies the facial constraint R. The weight w is used to indicate the constrained pixel, where $w \in [0, 1]$. A larger weight value indicates that the values of M and R will be more similar. In R, the constrained region is determined by the extracted facial features, as shown in the top row of Fig. 4.

The second term in (1) is the smoothing term, which is responsible for keeping the gradients of the mask M as low as possible, except across the significant gradients in G. We generalize the guided image from the original model of Lischiniski *et al.* [5] to a guided feature space, which means that richer facial information can be used to guide the propagation. Equation (2) shows the details of the smoothing term, where the subscripts x and y denote the spatial differentiation of M and G. $\|x\|_p$ represents the p norm in a guided feature space, that is, $\|x\|_p = (\sum_{i=1}^n |x_i|^p)^{1/p}$, if $x = [x_1, x_2, ..., x_n]^T$. When the guided feature space degenerates to a guided image and $p = 1$ at the same time, we obtain the original model in [5], where $\|G_x\|_p = |G_x|$ and $\|G_y\|_p = |G_y|$.

Note that more sophisticated metrics could also be integrated into our model, such as the *distances* that are derived from clustering [3], [4], manifold learning [2], [52], or metric learning methods [54], [55]. In our current guided feature space, the propagation effects are globally similar when p is set to a small positive value (e.g., $p = 1$ or $p = 2$). Since constructing a guided feature space with an appropriate metric is still an open problem, we adopt $p = 1$ in this paper and further analysis is left for our future research.

Three parameters control propagation in the smoothing term: ε is a small constant that prevents division by zero, λ is used to balance the relative weights of the two terms, and

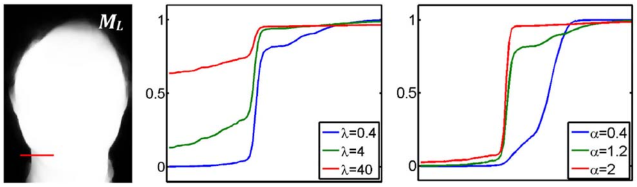

Fig. 5. Effect of the parameters on the lighting mask (LMsk) generation. The leftmost image is the LMsk of the input image in Fig. 3, whose parameters are $\lambda = 0.4$, $\alpha = 1.2$, and $\varepsilon = 0.0001$. The mask values along the red horizontal line are plotted for different values of λ and α.

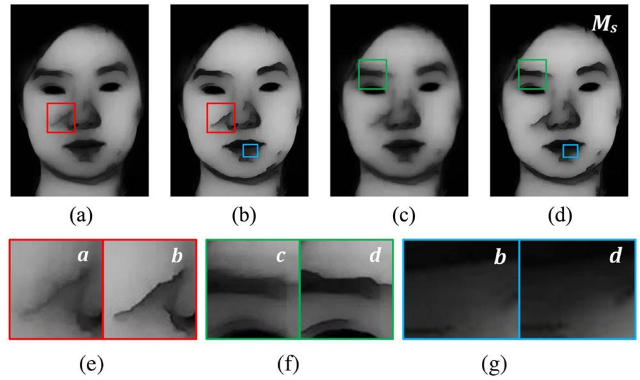

Fig. 6. Smoothness mask generation in different α and G. (a) $\alpha = 1, G = I_{L*}$. (b) $\alpha = \alpha_s, G = I_{L*}$. (c) $\alpha = 1, G = G_s$. (d) $\alpha = \alpha_s, G = G_s$. (e) Zooming patches of (a) and (b) with the same guided feature $G = I_{L*}$. (f) Zooming patches of (c) and (d) with the same guided feature $G = G_s$. (g) Zooming patches of (b) and (d) with the same parameter $\alpha = \alpha_s$. The parameter α is homogeneous in (a) and (c) whereas it is inhomogeneous in (b) and (d). For the guided feature G, only the luminance channel was used in (a) and (b) whereas the chromaticity channels were also considered in (c) and (d). (e) and (f) Close-ups demonstrate that better edge preserving could be obtained using the spatially variant α_s, and (g) indicates that better propagation effect could be achieved using the guided feature space G_s that contains richer facial feature.

α controls the propagation sensitivity to the gradients of G. Parameter ε is set to its typical value $\varepsilon = 0.0001$ [5], and the effect of the parameters λ and α is illustrated in Fig. 5. When λ increases, the difference of the mask values between the face (white) and nonface region (black) is reduced, which means more edit effects of the face region are propagated to the background. In contrast, when α increases, the transition between the face region and background become much shaper. In this paper, we extend the original homogeneous α to a spatially variant function $\alpha(z)$, which means that richer facial priors can be exploited to guide the adaptive propagation process during region-aware mask generation. During mask generation, different setting combinations of λ, α, and G are implemented according to the specific facial layer manipulation.

A. Lighting Mask

To generate the LMsk, we set $\lambda = 0.4$ and $\alpha = 1.2$, and we use the logarithm of the lighting layer as the guided image, that is, $G = G_L = logI_L$.

The input facial constraint R_L and the output LMsk M_L are shown in Fig. 4(a), which shows that although the editing region can be located roughly using the extracted facial feature in R_L, boundary fitting is not an easy task, especially in a region where the boundary is fuzzy and complex. However, M_L could fit the facial boundary closely as long as the edit information of R_L can be propagated in a suitable manner.

Note that the intensity of the mask indicates the edit degree of the operation, where a brighter region will be adjusted more.

B. Smoothness Mask

During skin smoothness enhancement, we need to handle some highly complex situations. For example, unwanted textures such as wrinkles or spots need to be removed whereas significant facial information must be preserved, such as details of the eyes, hair, or beards. Therefore, more meaningful facial features are extracted as the input constraint R_s, as shown in Fig. 4(b).

To generate the smoothness mask, the guided feature is constructed using the facial lighting and the color feature as follows:

$$G = G_s = (I_{L^*}, I_{a^*}, I_{b^*})$$

where I_{L^*}, I_a, and I_b are the normalized luminance and chromaticity channels of the input image in CIELAB space.

We use $\lambda = 0.1$ and $\alpha = \alpha_s(z)$ as the model parameters. In $\alpha_s(z)$, the initial values of the constraint regions are set to 0.01 whereas the values of the other regions are 1. Next, the Gaussian filer is applied so that the values in $\alpha_s(z)$ can be changed smoothly.

To demonstrate the effectiveness of the inhomogeneous parameter α_s and the guided feature G_s, we performed a comparison in different settings, as shown in Fig. 6. In a setting with the same guided feature ($G = I_{L^*}$ or $G = G_s$), the close-ups shown in Fig. 6(e) and (f) illustrates that better edge-preserving effects were obtained using inhomogeneous $\alpha = \alpha_s$ with more spatial priors compared with homogeneous $\alpha = 1$. When we used the same model parameter ($\alpha = \alpha_s$), different guided feature spaces, $G = I_{L^*}$ and $G = G_s$, produced globally similar facial masks. However, the guided feature space with richer facial information produced a better propagation effect in some local regions, as shown in Fig. 6(g). This suggests that constructing a higher-dimensional guided feature space containing more facial descriptors may improve the region-aware property of the mask, which is a possible direction for future work.

C. Color Mask

The process used to generate the color mask is similar to that employed to produce the smoothness mask, where $\lambda = 0.8$, $\alpha = 1$, and $G = G_c = (I_{L^*}, I_{a^*}, I_{b^*})$, as shown in Fig. 4(c). We perform more color manipulations in the nose, mouth, and skin regions whereas we retain more of the eyebrow, eye, and nonface regions.

V. Image Layer Manipulation

Using the region-aware mask, we can perform specific facial beautification to achieve skin smoothness, lighting, and color enhancements in an effective manner. Our system provides the user with interactive and automatic beautification schemes. Interactive manipulation allows the user to customize portraits by fine tuning, while automatic manipulation provides general

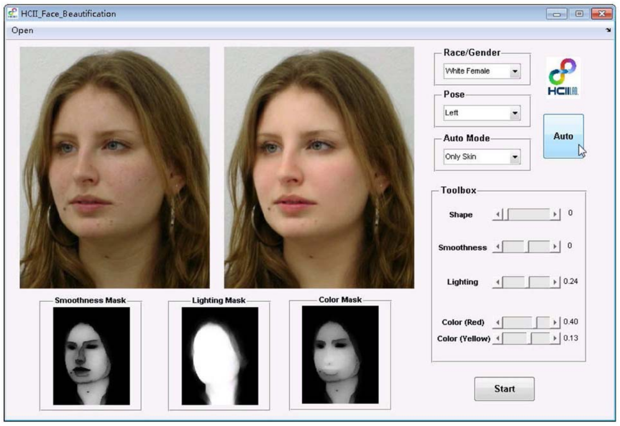

Fig. 7. GUI system for facial skin beautification with both automatic and interactive manipulation schemes. Here, we illustrate a screenshot of a prototype of our facial skin beautification application. Currently, the system performs automatic facial skin beautification in terms of smoothness, lighting, and color for a White female portrait with a left pose. The *Toolbox* panel shows the automatic optimized parameter combination, where a user could perform customized adjustment interactively using the sliders.

parameter optimization for faces with different genders, ethnicity, and pose.

A. Interactive Layer Enhancement

For consistency, we denote the detail, lighting, and color layers of the input image as I_s, I_L, and I_c; the corresponding facial masks as M_s, M_L, and M_c; and the manipulation outputs as O_s, O_L, and O_c, respectively. The enhancement of the layers is implemented as follows:

$$\begin{cases} O_s = & I_s(1 - T(M_s)w_s) \\ O_L = & I_L(1 + T(M_L)w_L) \\ O_c = & I_c(1 + T(M_c)w_c) \end{cases} \tag{3}$$

where w_s, w_L, and w_c are scalar values employed for interactive user adjustment.

During layer enhancement, the scalar values $w_{\{s,L,c\}}$ are used to control the global adjustment degree, where the output portrait remains unchanged if they are set to zeros. The layer masks $M_{\{s,L,c\}}$ are used to determine the relative adjustment between different regions, and more flexible manipulations can also be obtained if we apply an intensity transformation $T(\cdot)$ [11] to the masks. For example, we could use the Gamma curve $T(M, \gamma) = M^\gamma$ to change the relative weight (intensity) of the mask based on the parameter γ. In a special case, we would obtain a global homogeneous adjustment if the layer mask is set to one ($T(M_{\{s,L,c\}}) = 1$). In this paper, we simply used the original layer mask for skin enhancement, that is, $T(M_{\{s,L,c\}}) = M_{\{s,L,c\}}$.

B. Automatic Layer Enhancement

It is useful to perform automatic parameter optimization before user-customized adjustment. To enhance the smoothness, we initialize $w_s = 1$ because homogeneity is positively correlated with the perceived attractiveness [43], [45]. To enhance the lighting and color (w_L and w_c), we propose an intuitive and effective histogram-based method for estimating a suitable combination of parameters.

First, an average face is generated from an offline database collection, which is sorted according to gender (male/female) and race (Caucasian/Asian). After locating the landmarks, the average face is aligned to the input face by affine transformation and multilevel free-form deformation warping [49]. Second, we select the skin pixels of the input and average face using the region-aware mask, compute their differences, and produce a 10-bin histogram based on the residual values. Finally, the parameter w_L or w_c is obtained by summarizing all of the bin values, which are weighted according to their relative frequencies.

This simple data-driven approach based on an average face image is valid, but it does not perform well in many cases. Therefore, we truncate the residual values according to certain lower and upper bounds, which are based on psychological studies (knowledge-based priors). During lighting level manipulation, female faces are more attractive when the lighting is brighter in their skin regions whereas male faces exhibit the opposite trend [47]. Thus, we truncate the residual values in a range of $[0, h_L]$, where $h_L = 2$ is typical for females and $h_L = 0$ for males. Therefore, we tend to increase the lighting level for females whereas it remains unchanged for males, that is, $w_{L_{\text{female}}} \geq 0$ and $w_{L_{\text{male}}} = 0$. During color enhancement, more skin redness and yellowness can increase the attractiveness of female and male faces [44]–[46]. Similar to lighting enhancement, we truncate the residual values within a range of $[0, h_c]$ (typically $h_c = 2$). Thus, we tend to increase the skin redness and yellowness during skin color manipulations for females and males, that is, $w_{c_{\text{female}}} \geq 0$ and $w_{c_{\text{male}}} \geq 0$.

VI. Experiment

We constructed a GUI system to access our facial skin beautification method, which is shown in Fig. 7. This system facilitates automatic and interactive manipulation.

During automatic skin manipulation, a user can select appropriate facial attributes from the pop-up menus (see Fig. 7). In the present implementation, the *Race/Gender* menu contains four items (White Female, White Male, Asian Female, and Asian Male) and the *Pose* menu contains three items (Front, Left, and Right). Since facial structure is a significant component of facial attractiveness enhancement, shape beautification of a frontal face view is also integrated in our system, which can be activated using the *Auto Mode* menu, which contains three items (Only Skin, Only Shape, and Full Auto). After automatic beautification, the user can perform customized adjustments using the sliders in the *Toolbox* panel.

Note that the GUI system and editing tools could have been made more sophisticated, but this was beyond the scope of this paper. Using this system, we tested our method with a great variety of face images and compared our results with those produced using related methods and generated by representative commercial systems.

A. Basic Evaluation

1) *Qualitative Evaluation:* The qualitative experimental evaluation for our method was performed on three representative face datasets, that is, the Caltech [18], the Lifespan [57],

Fig. 8. Facial skin beautification for faces with different gender, ethnicity, age, background, and pose. (a) Input portraits. (b) Our results. The two leftmost faces were taken from the Caltech database [18], the two middle were taken from the Lifespan database [57], and the two rightmost were collected from the FEI database [19].

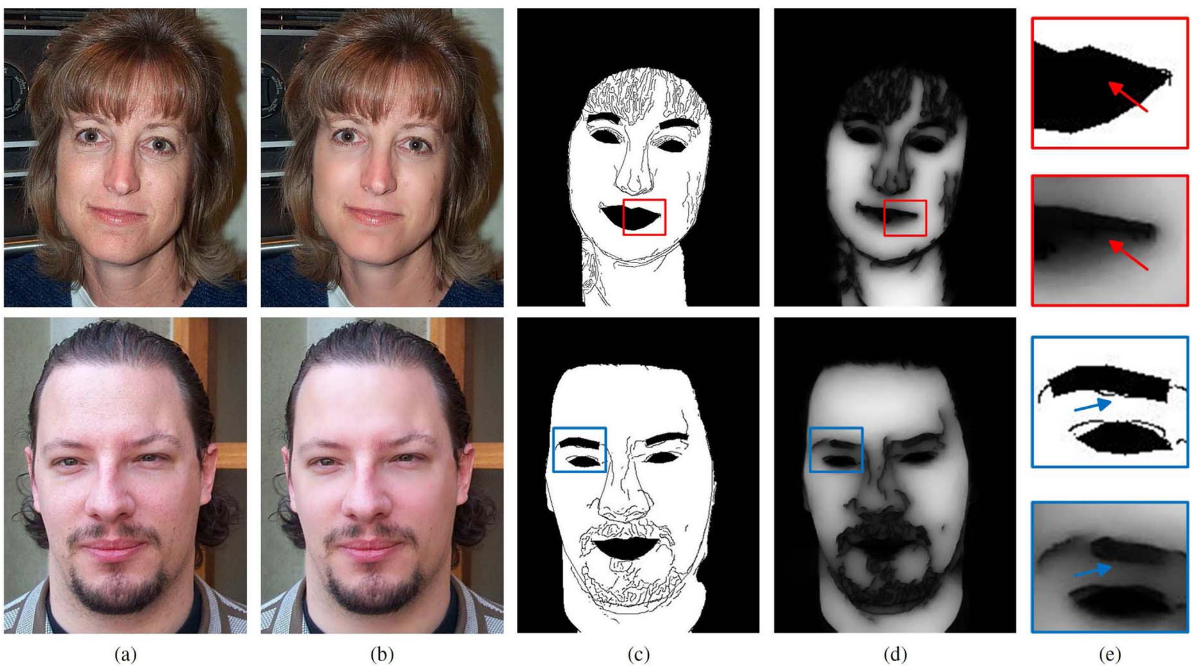

Fig. 9. (a) Input images taken from the Caltech face database [18]. (b) Results obtained after skin smoothness enhancement. (c) Input constraint in a coarse manner. (d) Smoothness masks with nicely fitting boundary that were produced by our adaptive edit propagation method. (e) Close-up images that illustrate the region-aware effect of our method.

and the FEI [19] database. The Caltech dataset contains frontal faces with different backgrounds, lightings, expressions, and genders; the Lifespan dataset contains frontal faces with large age variance and different ethnicity; and the FEI dataset contains faces with different poses and genders. To evaluate our facial beautification system under a real-world condition, we only eliminated the testing faces with extreme lighting, expression, and pose variances in the experiments.

We conducted automatic skin beautification using portraits that varied greatly, as shown in Fig. 8. The results demonstrate that our method is highly effective for facial skin enhancement in terms of the lighting, smoothness, and color. Unwanted wrinkles and spots on the skin were removed effectively whereas significant details and attributes were retained in the nonskin regions. Furthermore, the testing faces included various gender (female and male), ethnicity (Caucasian and Asian), age (young and senior), background (uniform and complex), and pose (left, front, and right) types, which demonstrates the broad generalizability of our method.

To further evaluate the effectiveness and robustness of the region-aware mask with variable facial characteristics, we tested our mask-generation method using face images with complex texture regions (such as hair and beards) and different poses. Fig. 9 shows the results obtained after we performed

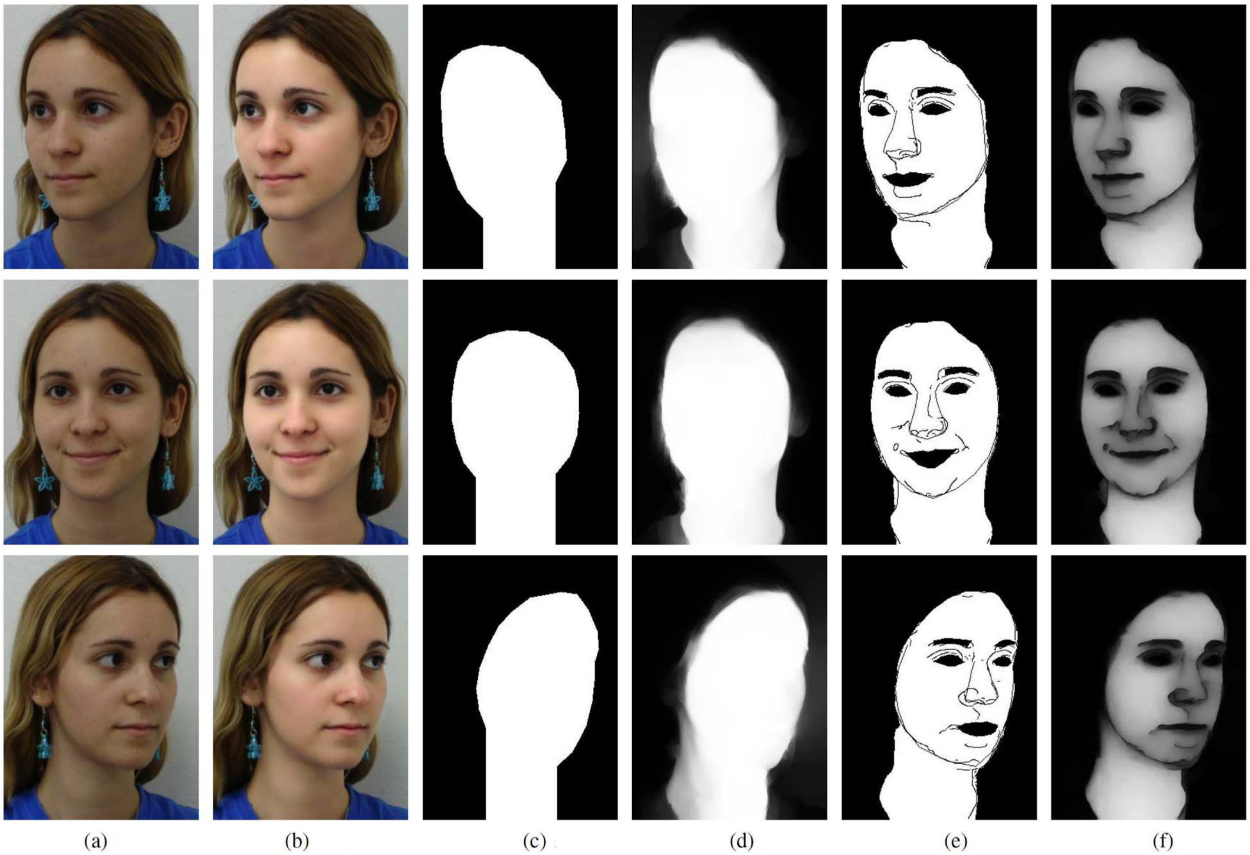

Fig. 10. Skin beautification for a female with different poses, taken from the FEI face database [19]. For consistency, R_L and M_L denote the input and output of the LMsk; R_s and M_s denote the input and output of the smoothness mask. The results illustrate that our method is robust to pose variation, as long as the input constraint locates the significant facial feature in a coarse manner. (a) Original. (b) Beautified. (c) R_L. (d) M_L. (e) R_s. (f) M_s.

smoothness enhancement using an image of a female with hair occlusion and a male with a beard. The input constraint only selected the preserved regions in a coarse manner but the mask fitted the boundaries accurately and yielded a smooth transition. Fig. 10 shows beautification of the same female in a different pose. The results demonstrate the robustness of our method with respect to pose variation.

2) *Quantitative Evaluation:* We made a quantitative experiment to evaluate the accuracy of our mask selection on a subset of the LFW-s database [59], which contains 2927 coarsely aligned faces with superpixel-wise hair/skin/background labels for face segmentation. The original LFW-s is divided into training, validation, and testing sets that contain 1500, 500, and 927 samples, respectively. To simplify our analysis, we converted hair labels to background labels and selected 600 faces without much hair and pose occlusions from 927 testing samples for our skin/background segmentation evaluation.

First, we used the ASM and the corresponding LMsk to perform skin/background segmentation. Since the evaluation of LFW-s is superpixel-wise, the pixel-wise results of the original ASM and LMsk were mapped to superpixel-wise segmentation according to the dominate pixel labels in one superpixel. The accuracy of the baseline ASM segmentation is 92.49% while the LMsk is 95.32%. The results indicate that our adaptive mask can effectively improve the skin selection accuracy of a simple ASM detector, which is consistent to our qualitative evaluation (e.g., R_L and M_L in Fig. 10).

Second, we compared the LMsk with two automatic facial skin segmentation methods: the standard CRF [58], [61] and the conditional restricted Boltzmann machine (CRBM) [59]. Both the methods are based on the same superpixel-wise node features and edge features [59]. After model training and parameters selection, the accuracy of the CRF is 97.63% while the CRBM is 97.93%. Although high accuracy of superpixel-wise skin segmentation dose not guarantee high performance of facial beatification, the results indicate that we can probably further improve the performance of our region-aware mask using richer facial features and more sophisticated learning methods.

3) *Computation:* Our un optimized MATLAB implementation of the facial beautification system takes totally about 12 s for a 500∗600 facial image on a 2.5 GHz Pentium(R) Dual-Core E5200 processor with 2GB of memory. During the facial manipulation, it takes about 8 s to generate all the three layer masks. Note that highly efficient implementation could be obtained when more sophisticated numerical methods are used for mask generation, for example, locally adapted hierarchical basis function preconditioners [63].

B. Comparisons With Related Methods

Fig. 11 shows a comparison of skin smoothing enhancement using the method proposed by Lee *et al.* [26] and our method. The results are similar but our method preserved more details in the region boundaries and the smoothing effect was better

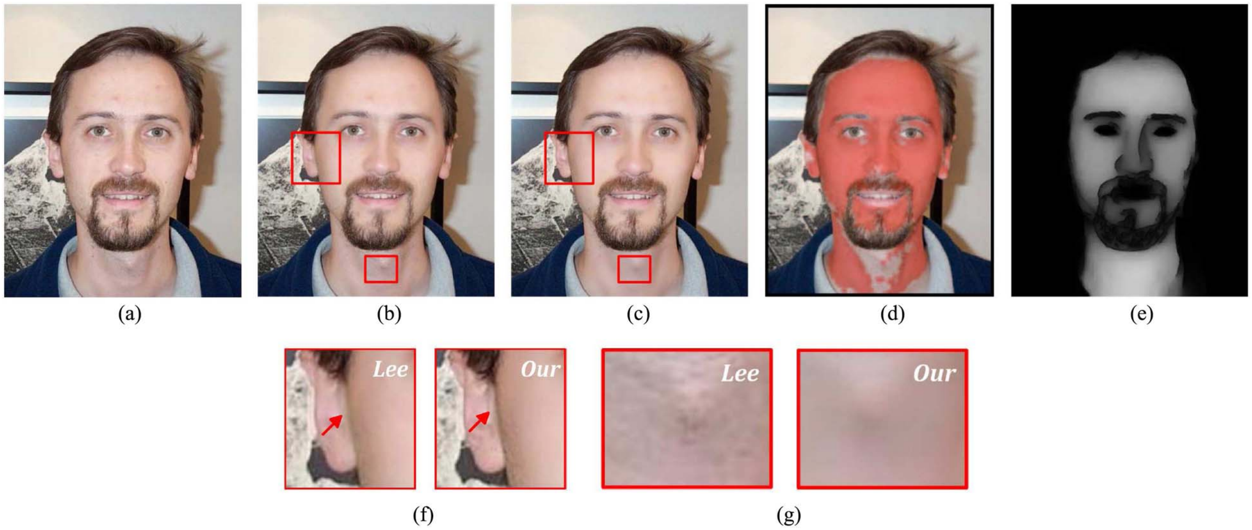

Fig. 11. Comparison with the method of Lee *et al.* [26]. It shows that our region-aware mask selects the edited region with more precision. The close-up images indicate that our method obtains better detail preservation in (f) region boundary and better smoothing effect in (g) skin region. (a) Original. (b) Lee *et al.* [26]. (c) Our result. (d) Lee's mask. (e) Our mask.

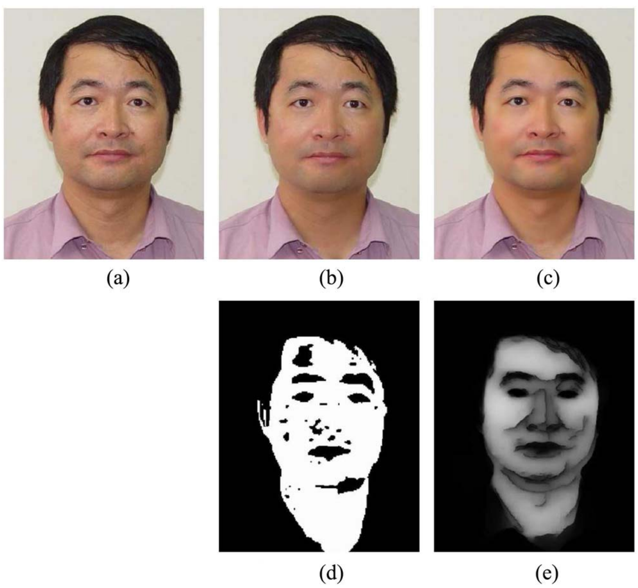

Fig. 12. Comparison with the method of Chen *et al.* [25]. It shows that our method not only generates a facial mask with more precision but also produces a face with better skin property. (a) Original. (b) Chen *et al.* [25]. (c) Our result. (d) Chen's mask. (e) Our mask.

in the skin regions, as shown in the close-up images. These differences are attributable to the mask-generation models. In the skin segmentation method proposed by Lee *et al.*, a GMM of pixel colors (RGB) is used as the prior for Bayesian segmentation. However, highly textured facial regions such as hair or beards may lead to unstable parameter estimation by the GMM. By contrast, our method resulted in better edge preservation in the boundaries and more effective continuity within the skin regions.

Fig. 12 shows the facial color and smoothness enhancement results obtained with the method proposed by Chen *et al.* [25] and our method. Our method appeared to make the subject look *healthier* because we used the average face as the prototype for skin beautification and we also integrated relevant psychological knowledge into our automatic manipulation scheme. In addition, subtle details in some regions were preserved better using our method, such as the Adam's apple.

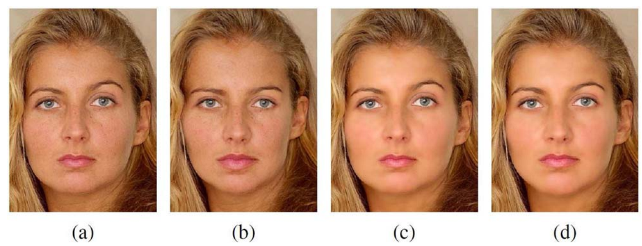

Fig. 13. Comparison with the method of Leyvand *et al.* [34]. (a) Original image. (b) Result obtained after facial structure beautification, taken from [34]. (c) Result produced by our skin beautification method. (d) Result produced by our skin beautification method with facial shape enhancement.

Fig. 13 shows a comparison of the results obtained using the facial geometry beautification method proposed by Leyvand *et al.* [34] and our facial skin beautification approach. The results demonstrate that both methods increased the facial attractiveness to some extent and it seems that our method is complementary to that proposed by Leyvand *et al.* [34]. Therefore, we reproduced a similar geometry enhancement module [34] and integrated it into our current system. The results obtained using this integrated system suggest that a combination of facial geometry and skin manipulation could improve the facial attractiveness significantly, as shown in Fig. 13(d).

C. Comparisons With Commercial Systems

We compared our method with three representative commercial systems, that is, PicTreat [15], Portrait+ [16], and Portraiture [17], as shown in Fig. 14. Since each system employs its own distinctive facial-editing process, it was

(a) (b) (c) (d) (e)

Fig. 14. Comparison with commercial systems PicTreat [15], Portrait+ [16], and Portraiture [17]. In PicTreat, we manipulated the images using the website [15]. In Portrait+, we chose the preset style of *cleanse2 & beautify* for the female and *cleanse2 & tanned skin* for the male. In Portraiture, we simply edited the face using its default setting. In our system, we beautified the face using the automatic scheme according to the facial attributes of the input portrait. (a) Original. (b) PicTreat [15]. (c) Portrait+ [16]. (d) Portraiture [17]. (e) Our results.

difficult to make a comparison using exactly the same settings. Therefore, we selected the most similar beautification scheme for each system in this experiment.

For PicTreat, we uploaded the original face images to the website [15] and obtained the results. For Portrait+, we performed face manipulation using a PC-based application. Portrait+ provides various schemes for face image enhancement, so we selected the most similar to our method. For females, we used the preset style of *cleanse2 & beautify*, while for males, we used *cleanse2 & tanned skin*. Portraiture was run as a plug-in in Photoshop CS6 (64 bit) and we simply used the default settings for automatic manipulation.

Fig. 14 shows the results for two testing face images with different poses and genders, which were obtained from the FEI database [19]. The results show that all of the systems were effective for facial skin beautification. However, there were also some apparent differences among their results. PicTreat globally adjusted the lighting and the color of an image, while its smoothness enhancement appeared to be slightly inferior to that of the other methods. Portrait+ and Portraiture preserved the original image lighting and they applied highly effective smoothness manipulation schemes to remove unwanted facial wrinkles and spots. Our method was comparable to the commercial systems and superior in several respects. Our region-aware mask yielded natural and complete smoothness, lighting, and color enhancements in the local skin regions. Our automatic parameter optimization scheme is based on psychological knowledge [43], [44], which means that our results are consistent with the common principles of facial beauty.

VII. Conclusion

In this paper, we developed a powerful unified framework for specific facial beautification in terms of the skin smoothness, lighting, and color. In our framework, region-aware masks are generated using an adaptive edge-preserving energy minimization method. The region-aware mask allows the user to perform more flexible and effective skin manipulations.

At present, our system can obtain desirable automatic beautification effects for most frontal face images without any user interventions. However, some user modifications may be required for face images in different poses and those with variable lighting or expressions, because the ASM method may fail to locate the landmarks with sufficient accuracy. However, the use of a more sophisticated landmark detector [7], [8] could facilitate beautification with greater robustness.

Another limitation of our current feature extraction method is the simple assumption that significant edges in the lighting layer are caused by meaningful facial attributes, such as expressions, beards, or hair. In some situations, however, these edges may also be caused by unwanted details. For example, if an image of a senior person with a characterful face is subjected to skin smoothness beautification, the current method may fail to recognize the wrinkles to be removed. However, if more semantic facial attributes [9], [10] could be integrated into the input constraints, the generated mask would yield better region-aware effects.

In this paper, a region-aware mask was designed for specific facial skin enhancement, but the mask generation framework could be applied to more general image manipulation problems, such as image-based shaving [9] or digital face makeup [29]. A new adjustment mask can be produced by freely replacing the current feature extraction or edit propagation approach with other methods. It would be useful to produce a region-aware mask for general image manipulation in future research.

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