Journal of Information Hiding and Multimedia Signal Processing ©2015 ISSN 2073-4212
Ubiquitous International Volume **6**, Number **6**, November **2015**

Framework for Automatic Face Makeup Rendering for Fixing Flaws in Images

Ju-Chin Chen * and Tzung-Hua Wu

Department of Computer Science and Information Engineering
National Kaohsiung University of Applied Sciences,
Kaohsiung, Taiwan, R.O.C
*Corresponding author: Ju-Chin Chen
jc.chen@cc.kuas.edu.tw

Received March, 2015; revised May, 2015

Abstract. *Because smartphones have become one of lifes necessities, photos are gradually used in the place of texts to record all the moments of ones daily life. For various reasons, including sharing photos with friends, we require postprocessing or manual editing of images. However, this work, which includes the editing of many photos, is highly time-consuming for amateurs. Thus, in this paper, we develop a framework to create a batch of face makeup by referring to one example. Moreover, we propose four makeup algorithms for facial flaws, including color adjustment for eyebrows and lips; removal of freckles, moles, and dark circles; and smoothing of skin flaws. More precisely, first, we consider one reference example that can be manually edited and estimate a recovered mask that records the pixels of the makeup region to be processed. Then, feature landmarks on the reference example and a subject image are detected with the ASM algorithm, and the geometric relationship between these two images is modeled by an affine transformation. By transferring the pixel location of the makeup region from the reference example, the makeup region in the subject image can be estimated, and the corresponding makeup algorithm can be applied. The advantages of the proposed framework are that only one reference image is required, and the virtual makeup can be automatically rendered for the remaining images of the same person. The experiment results demonstrate the effectiveness of the proposed framework for fixing flawed images.*

Keywords: Face makeup; Active shape model; Bilateral filter.

1. **Introduction.** As smartphones become one of lifes necessities, photographing becomes the most popular method of recording all the moments of ones life. Using photos, people can record every moment for themselves and their family and friends, and these images become treasured memories. Most people have a desire to look attractive, and face makeup is a technique that improves ones beauty. However, enhancing the appearance with physical face makeup is difficult for ordinary users. Thus, using editing softwares, such as Adobe PhotoshopTM, provide an alternate method to improve ones appearance and edit ones photos as a kind of virtual makeup.
Now, consider this scenario: one ordinary user goes for a trip for one week with his/her family and clicks many photos. However, during this trip he/she got sick and did not sleep well. As a result, this user appears to be in pain and is spotted with dark circles in every photo. Thus, this user has to perform postprocessing on each image to confidently share his/her trip photos. For amateurs, producing one consistent set of delicate virtual

makeup operations that include many procedures is time-consuming, including concealing flaws or moles, smoothing skin or erasing dark circles, and recolorizing eye shadow and lips; moreover, the same processes have to be repeated every time to edit a batch of photos.

In this paper, we develop a framework to automatically edit a batch of face makeup by referring to one example, which can be either manually edited or obtained from other systems or softwares [1], [2], [3]. According to common face makeup applicationsloose powder to change the skin texture, foundation to conceal flaws and moles, and color makeup, such as lip gloss, eyeliner, and eye shadowwe propose four makeup algorithms to smoothen the skin region and recolorize feature components (eyebrows, eyes, and lips). By the construction of the geometric relationship between the reference example and the subject image, the makeup region on the subject image can be estimated, and the corresponding makeup algorithm can be applied.

2. **Related Work.** Because the population of smartphone users rapidly increases, more commercial applications and software related to photo editing are developed [2]-[9]. Among them, virtual makeup is an interesting application; moreover, applications such as Taaz [3] and ModiFace [6] can simulate the effects of physical makeup with some manual guidance. Furthermore, researchers devoted to virtual makeup propose the frameworks [1], [10], supported by the idea of image analogies [11], [12], to render a new image by learning the effects of pixel changes, i.e., before and after makeup, from a pair of examples. Tong *et al.* [1] simulated the makeup face learned from a pair of examples of the same person, which are taken in the same position, expression, and lighting environment. Then, the quotient image, which represents a change between the before and after makeup images, is obtained by dividing the after makeup image by the before makeup image and is used to estimate a new makeup image. Tsumura *et al.* [13] extracted the components of hemoglobin and melanin, and inpainted them to provide the effects of anti-aging and tanning. Schebaum et al. [14] provided a makeup suggestion according to the optimization result learned from a professional "before-and-after" pair dataset. In contrast with the framework of virtual makeup learned from a pair of examples, Guo et al. [11] developed a system that considers only the after makeup image example, which is not only more convenient but also copes with inappropriate results due to various facial textures across faces. The system provides texture and color transfers, while the face structure can be preserved via a three-layer face decomposition. However, manual landmark adjustment is required [15]. Based on the framework of [11], Xu *et al.* [15] detected face landmarks with an existing algorithm, and they automatically adjusted the facial landmarks with skin color segmentation based on the Gaussian mixture model. In addition, there are approaches and free APIs could automatically locate as many as 50+ face landmarks even determine the eyebrow, lip, eye regions, etc., for example API of face++ [16].

Some studies propose the automatic beautification of faces in photos. Brand and Pletscher [17] proposed algorithms using conditional random fields to detect and remove the flaws and moles from faces in photos. Leyvand *et al.* [18] transferred the texture across faces and smoothed wrinkles using anti-aging algorithms [19], [20]. Going beyond texture modification, Schebaum *et al.* [14] changed the face structure for attractiveness after being trained with many attractive faces, and Chou *et al.* [21] proposed a face-off algorithm to replace facial components (for example, replacing a closed mouth with a laughing one and a flat nose with a tall one.). Image inpainting is another topic related to our work. Various algorithms have been proposed to fill in the destroyed or missed regions on scene images [22], [23], [24], [25]. Facial images, which differ from scene images, require not only texture synthesis but also the preservation of the facial structure. Studies [26], [27] can compensate for a region of missed pixel information based on surrounding pixels; even the eyeglasses can be removed and the missed region can be filled [28] to improve the performance of face recognition.

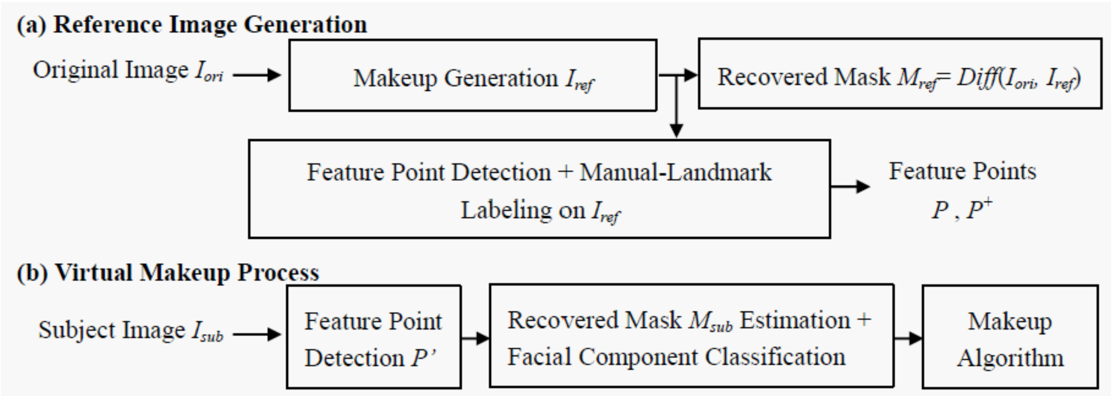

FIGURE 1. The proposed virtual makeup framework. (a) Reference image generation process (b) Virtual makeup process

3. **System Overview.** Figure 1 shows the proposed framework for the virtual makeup, which consists of two processes: the first process is to generate the reference image I_{ref} and feature point information (Figure 1(a)), and the second process refers I_{ref} to conceal the facial flaw on the subject images (Figure 1(b)). In the reference image generation process, one flawed image with the imperfection blemish I_{ori} can be manually processed via software [3], [5]; the resulting image is denoted as I_{ref} for the following reference. Then, the makeup regions, represented by the recovered mask M_{ref}, can be estimated based on the difference between I_{ori} and I_{ref}. To align the reference image with other subject images, 9 feature points, denoted as P, are automatically detected on I_{ref} [29]. Moreover, for the dedicated makeup, more control points can be manually labeled, and thus precise facial regions can be defined via 14 manually labeled feature points, P+, which adds four points for each eyebrow, two points for each eye, and two points for the corners of the mouth. Note that the manual process is only performed in the reference image generation process. Following that, the virtual makeup process can be performed automatically on other subject images,I_{sub}, taken at the same duration and with the same imperfection blemish as the reference image. Nine feature points, P', are detected on the subject image, and the geometric relationship between the reference image, I_{ref}, and the subject image, I_{sub} , can be constructed based on P and P'. Then, according to the makeup region on the reference image, the facial components that require makeup are classified, and the corresponding makeup algorithm can be applied. Note that four makeup algorithms are proposed to adjust the color or texture information for the corresponding facial component.

4. **Framework of Face Makeup.** By referring to the one example provided by the user, in this study, our aim is to develop a framework to automatically provide virtual makeup for those facial images with an imperfection blemish, called the subject images. The major challenges are how to detect the facial components that need to be recovered on the subject image and the seamless makeup without looking artificially; that is, not only the pixel values of the reference image are to be considered, but the contents of the subject image need to be examined. Considering one subject image with facial flaws and by manually performing some virtual makeup processes produces an image called the reference image

FIGURE 2. Figure 2. Example of manual virtual makeup. Left: The original image. Middle: The reference image, which is manually edited to recolorize eyebrows and lips and remove dark circles. Right: Recovered mask M_ref for the estimated makeup region

in our work. Then, by constructing a geometric relationship between the reference image and the subject image, the facial components that require to be adjusted on the subject image are classified, and the corresponding makeup algorithm can be applied.

4.1. **Makeup Region Detection.** Some research into flaw and mole detection has been conducted [30], [31]; however, the process of professional makeup is more complicated, which might consist of re-colorizing or reshaping the facial components and smoothing the facial texture. Figure 2 shows an example of both before and after virtual makeup, which consists of the manual processes of re-colorizing eyebrows and lips and removing dark circles. The reference image can be obtained by either detecting flaws automatically or manual editing. Then, the makeup region can be estimated as follows:

$$M_{ref}(x,y) = \begin{cases} 1 \ if \ |I_{ref}(x,y) - I_{ori}(x,y)| > \theta, \\ 0 \ otherwise \end{cases} \tag{1}$$

where $I_{ori}(x,y)$ and $I_{ref}(x,y)$ re the gray value of the pixel (x,y) on the original and reference image, and θ is a threshold value to ignore noise.

4.2. **Facial Image Alignment.** Because the image resolution or facial poses on the reference image and subject image may differ, facial image alignment is applied to match the facial components on these two images. First, nine feature points on the reference image and subject image are detected by an existing algorithm [29], which can detect two points on the corners of each eye and the mouth, and three points on the nose, as shown in Figure 3. Recolorizing or reshaping eyebrows is common in physical makeup. Although the location of eyebrows on a subject image can be estimated according to the geometric relationship constructed by nine feature points, a small error can cause unexpected effects.

Because the algorithm [29] can provide promising results despite some variance in lighting, facial poses, and expression, we decided to use the algorithm and manually label 14 other feature points on the reference image, as shown in Figure 3. An alternative method is to use other algorithms that can detect more feature points [16], [32], [33], [34]. Note that manual labeling is only performed on the reference image and not on the subject images. Then, the geometric relationship between I_ref and I_sub can be constructed by an affine transformation:

$$P' = AP \tag{2}$$

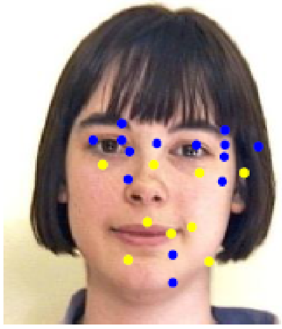

Figure 3. Feature points. Nine yellow feature points, shown in yellow, are automatically detected [29] and other 14 points, shown in blue, are manually labeled.

where A is a 3-by-3 affine transformation matrix capturing the rotation, translation, skewness, and scaling factors, and P and P' are 3-by-9 matrices that record pixel coordinates with homogenous representation for feature points on the reference image and subject image, respectively. Note that the geometric relationship is constructed using nine feature points. By transformation matrix A, 14 other feature points on the subject image can be estimated.

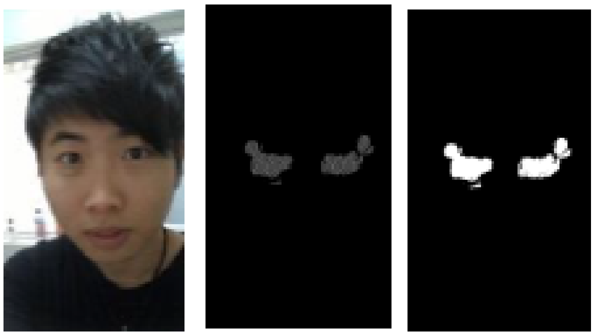

Figure 4. Left: One subject image. Middle: Makeup region estimated by forward mapping. Right: Makeup region Msub estimated by backward mapping.

After obtaining the geometric relationship between the two images, the makeup region on the subject image can be estimated by forward mapping the pixel of the recovered mask to the subject image, as shown in Figure 4. However, when the subject image is larger than the reference image, holes are observed within the makeup region. To cope with the missing information, backward mapping between I_ref and I_sub is applied, which is to classify whether the pixel on the subject image falls into the makeup region on the reference image. Thus, an alternative geometric relationship is constructed as follows:

$$P = A_{back}P' \tag{3}$$

Each pixel (x_{sub}, y_{sub}) on the subject image is transferred to the domain of the reference image, denoted as (x_{ref}, y_{ref}), and if six pixels surrounding (x_{ref}, y_{ref}) are labeled as a makeup region, the pixel (x_{sub}, y_{sub}) is labeled as a makeup region on the subject image. The term M_{sub} represents the makeup region on the subject image.

4.3. **Virtual Makeup Algorithms.** As shown in Figure 3, different face components, including eyebrows, eyes, nose, nostrils, lips, and facial skin, can be defined via these control points.

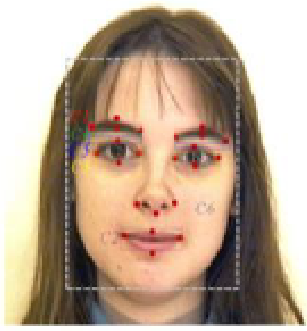

FIGURE 5. Facial components defined by control points, including eyebrows, eyes, nose, nostrils, lips, and other facial skin, and they are further divided into six classes, red as C1, purple as C2, yellow as C3, green as C4, blue as C5, and gray as C6 [8].

Moreover, when the makeup region on the subject image is estimated, the facial components belonging to the makeup region for the subsequent makeup are classified. Because the makeup technique for each component is different, we further divide the face components into six classes (C1 to C6), as illustrated by different colors in Figure 5, with each class treated using different makeup algorithms. As shown in the figure, C1 and C2 are the facial components denoting eyebrows and lips, respectively. C3 is the region of eyes, as well as the area below eyes with 0.8 times the height of eyes. The region between eyes and eyebrows are equally divided into the upper and lower regions, which is denoted by C4 and C5, respectively. C6 corresponds to the skin region, i.e., the entire face excluding C2 to C5. Note that classes C1, C2, C3, and C6 correspond to the makeup algorithm for eyebrows, lips, eyes, and skin, respectively, whereas C4 and C5 are auxiliary facial regions that employ the makeup algorithm for eyes.

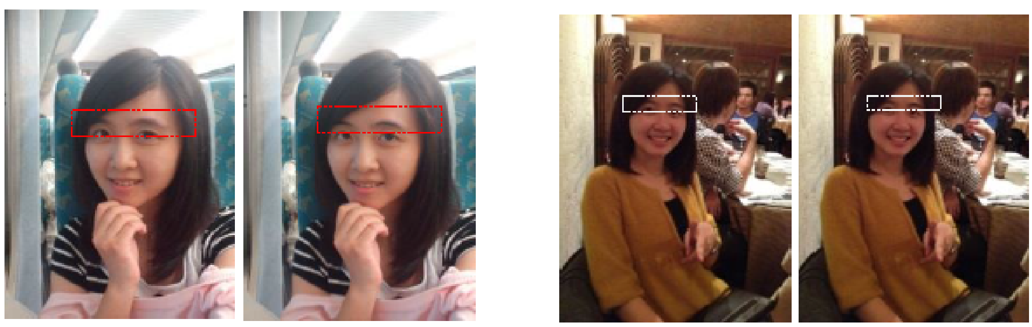

FIGURE 6. An example of the makeup for Eyebrows. Left pair: Original and reference images with the deeper color of eyebrows applied manually. Right pair: Subject image and the corresponding automatic makeup for eyebrows

4.3.1. ***Eyebrow Makeup***. Most physical makeup applied to eyebrows involves adjusting the color (deeper or lighter) and reshaping it (elongate or thin out). Thus, the virtual makeup for eyebrows can be described as follows:

$$I^c_{makeup}(x,y) = I^c_{sub}(x,y) + \delta^{eyebrow}(x,y)\,\Delta I^c(x,y) \;\; c \in \{R,G,B\} \tag{4}$$

where c represents one of the RGB channels, I^c_{makeup}(x,y) is the resulting image, $\Delta I^c(x,y)$ is the color difference between the original and reference images, and $\delta^{eyebrow}(x,y)$ is an indicator term with the value 0 or 1 which is defined as follows:

$$\delta^{eyebrow}(xy) = \begin{cases} 1 \; if\,(x,y) \in M_{sub} \;\wedge (x,y) \in C1 \\ \qquad 0 \; otherwise \end{cases} \tag{5}$$

The color difference $\Delta I^c(x,y)$ is defined as follows:

$$\Delta I^c(x,y) = \mathrm{r}\,(\mathrm{x,y})\,[I^c_{ref}\left(x',y'\right) - I^c_{ori}\left(x',y'\right)] \tag{6}$$

where (x', y') is the corresponding pixel of (x, y) on the original and reference image via the geometric relationship in Eq. (3), and r(x, y) is the image lighting ratio defined as $\gamma\,(x,y) = \frac{I_{sub}(x,y)}{I_{ori}(x',y')}$ where $I_{sub}(x,y)$ and $I_{ori}(x',y')$ are the gray values. By increasing or decreasing the difference for each color channel, the makeup for eyebrows can be obtained. Figure 6 shows an example of the virtual makeup for eyebrows.

4.3.2. ***Lip Makeup***. Most physical makeup applied to lips seeks to enhance the red color for a superior look. The makeup for eyebrows involves the adjustment of RGB channels; however, for lips, only the red channel is considered, which is given as follows:

$$I^R_{makeup}(x,y) = I^R_{sub}(x,y) + \delta^{eyebrow}(x,y)\,\Delta I^R(x,y) \tag{7}$$

where R represents the red channel, $\Delta I^R(x,y)$ is the difference in the red channel between the original and reference images, and $\delta^{lip}(x,y)$ is a 0 - 1 indicator to label the region of lips which is given as follows:

$$\delta^{lip}(xy) = \begin{cases} 1 \; if\,(x,y) \in M_{sub} \;\wedge (x,y) \in C2 \\ \qquad 0 \;\; otherwise \end{cases} \tag{8}$$

The color difference $\Delta I^R(x,y)$ in the red channel is defined as follows:

$$\Delta I^R(x,y) = \mathrm{r}\,(\mathrm{x,y})\,[I^R_{ref}\left(x',y'\right) - I^R_{ori}\left(x',y'\right)] \tag{9}$$

where r(x, y) is the image lighting ratio as defined in Eq. (6). Figure 7 shows an example of the makeup for lips. Note that only a closed mouth is considered in the present work, and that the processing of an open mouth requires more feature points on the mouth to cope with the mouth cavity.

4.3.3. ***Eye Makeup***. Mostly, physical makeup for eyes involves using an eye liner or eye shadow and the removal of dark circles. For the virtual makeup of eye shadow, the color information can be set into the corresponding makeup region, as shown in Eq. (4). However, if the concealment of dark circles is to be performed, direct color setting will result in inconsistent effects due to lighting variance between the reference and subject images. Thus, rather than referring to the reference image, refilling pixel information of dark circles has to refer the information from the subject image only. The region between the eyebrow and eye is equally divided into subregions. The upper subregion is defined as class C4, whereas thelower subregion is class C5, and Strategy1 and Strategy2 are applied to each class for precise pixel selection. For each pixel P(x, y) that requires makeup in C4, it is replaced by the mean of four pixels, including the corresponding right, lower-left, lower, and lower-right pixels, as shown in Figure 8(a), to avoid referring to the pixels of

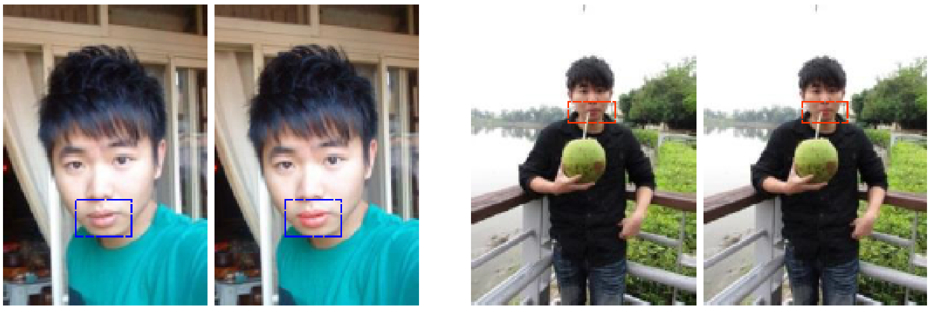

Figure 7. Lip makeup example. Left pair: Original and the reference image which is performed the enhancement color of lip manually. Right pair: Subject image and the corresponding automatic lip makeup

eyebrows. On the other hand, if the pixels are classified as class C5, they are replaced by the mean of the corresponding left, upper-left, upper, and upper-right pixels, as shown in Figure 8(b). If the pixel is in the makeup region below eyes, i.e., it is classified as class C3, the *Strategy3* is to replace the pixel value by the mean of the corresponding lower, lower-left, and lower-right pixels. Note that the starting pixels of the *Strategy1* and *Strategy2* for the region of classes C4 and C5 are the upper-right corner point and the lower-right corner point in the corresponding region. While, the filling strategy for class C3 starts from the pixels distant from eyes to replace the original deeper color due to dark circles. The filling strategies are performed twice in two directions (i.e., right-to-left and left-to-right) for smooth results.

Figure 8. The makeup strategy for pixels that lie between each eyebrow and eye. (a) Strategy1 for pixel as class C4. (b) Strategy2 for pixel as class C5.

Note that if the reference pixel belongs to an eye or eyebrow, it will be ignored. Although the feature points of eyes can provide its rough location, the segmentation of the complete eye regions require more feature points. Thus, the eye detector is proposed using the edge and color information. A Sobel operator is used, and the binary result can be obtained by setting the mean of the gradient magnitude as the threshold. The mean is computed within a region below the eye with 0.5 times the height and width of the eye. An example is shown in Figure 9. In addition, the color information of YIQ color space is used to segment the eye region. Figure 10 shows the binary results using the mean of Y and I values. Note that the region for computing means is the same as the one with the Sobel operator. In summary, the makeup applied for eyes is as follows:

$$I_{makeup}(x,y) = \begin{cases} Strategy\ 1\ if\ (x,y) \ \in M_{sub} \wedge (x,y) \in C4 \wedge EyeDetector\ r\ (x,y) = 0 \\ Strategy\ 2\ if\ (x,y) \ \in M_{sub} \wedge (x,y) \in C5 \wedge EyeDetector\ r\ (x,y) = 0 \\ Strategy\ 3\ if\ (x,y) \ \in M_{sub} \wedge (x,y) \in C3 \wedge EyeDetector\ r\ (x,y) = 0 \\ \qquad I_{sub}(x,y) \qquad Otherwise \end{cases} \tag{10}$$

where $EyeDetector(x, y)$ is a binary function, which returns 1 as the pixel belongs to the eye region, i.e., the gradient magnitude is larger than the mean value and the Y and I values of the pixel (x, y) in the YIQ color space are smaller than the mean values, and returns 0 for otherwise.

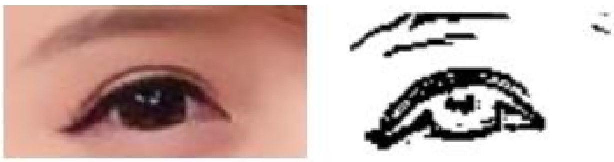

FIGURE 9. Left: Original image. Right: Binary result of eye detection by Sobel operator with the threshold value of the mean of gradient magnitude within a region below the eye with 0.5 times the height and width of the eye.

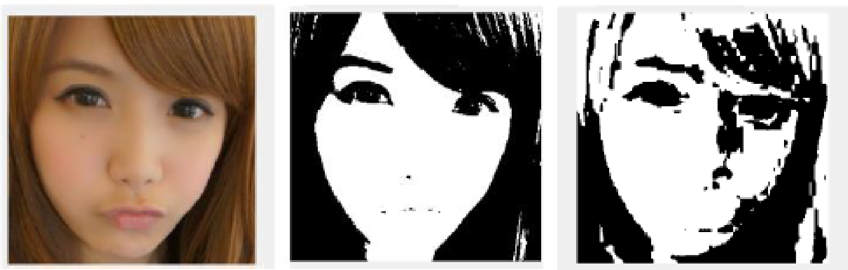

FIGURE 10. Left: Original image. Middle: Binary result in Y domain of YIQ color space.

4.3.4. ***Skin Makeup***. For physical makeup of the skin region, foundation and loose powder is used to cover up the original skin to make it look smooth and without flaws, moles, and pimples. Excluding the region of eyebrows, eyes, and lips, the remaining region belongs to the class of skin makeup. Virtual skin makeup can be divided into local skin makeup and global skin makeup; the former one is to conceal the flaws or moles labeled within the makeup region, whereas the latter one is performed on the entire skin region. The local flaws in the skin region, such as moles and pimples, can be concealed by filling from the surrounding pixels which are not labeled as local skin makeup, and the filling process stars from the most outside pixels of local skin makeup, as shown in Figure 11.

Note that to obtain a consistent result, the estimated makeup region belonging to class C6, the skin region, is dilated. That is, any pixel that has one pixel in its eight-pixel neighborhood labeled within the makeup region needs to be processed. Global skin makeup focuses on skin problems that cover larger skin regions, such as pockmarks and freckles. Not only must the skin region be smooth, but also the structure of the facial component should be preserved. Thus, the edge-persevering smooth algorithm can be

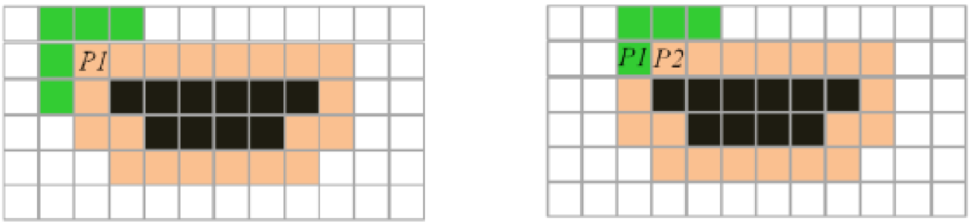

FIGURE 11. Left: Pixel P1 is processed. Right: Pixel P2 is processed.Right: Binary result in I domain of YIQ color space. The local skin makeup region is shown in black and the dilated makeup region is shown in light orange. The local skin makeup stars from the upper-left pixel of dilated makeup region, i.e. P1, and P1 is replaced with the mean value of surrounding valid pixels which are not labeled as makeup region, as shown in green. When P1 is processed, the next pixel P2 is replaced with the mean value of surrounding valid pixels as shown in green. Note that P1 is included.

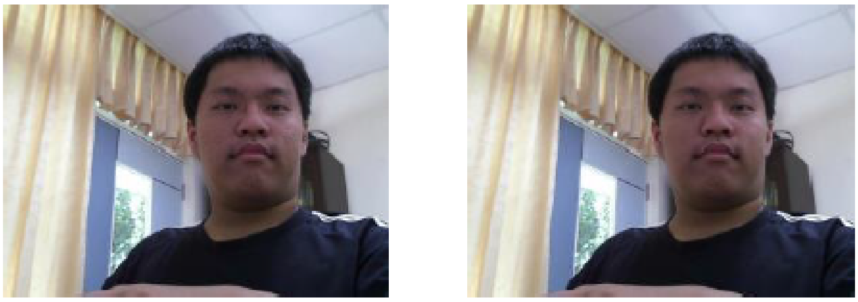

FIGURE 12. Left: Original image. Right: Global skin makeup via the bilateral filter [21].

applied [35], [36]. Now, we selected a bilateral filter, which considers the difference in the spatial and intensity domains simultaneously as follows:

$$I_p = \frac{1}{Z}\sum_{q \in S_p} G_s(p-q)\ G_{sr}(I_p - I_q) \tag{11}$$

where p is the coordinate of the processing pixel; q is the coordinate of the pixel belonging to the neighbors of $p; S_p, I_p$, and I_q are RGB color vectors; G_s and G_r are Gaussian distribution for the spatial and intensity domains, respectively, and the corresponding parameters are $(0,\sigma_s)$and$(0,\sigma_r)$; and Z is the normalization factor. As the distance reduces or similarity grows between p and q, the pixel q will be assigned a greater weight. The resulting image is shown in Figure 12. As shown in the original image, the flaws can be concealed, and thus a smooth skin can be obtained. The proposed algorithm is summarized in Figure 13.

5. **Experimental Results.** Personal photos collected form Facebook and Google search serve as a database for the makeup result analysis. According to the makeup algorithms for the facial components, the collected photos can be divided into four categories. To demonstrate the makeup capabilities, people with light-colored eyebrows, pale lips, dark circles, or larger areas of flaws are gathered. Because the feature point detection has a large effect on the makeup results, frontal and near-frontal faces are collected, whereas

```
Input: Original image I_ori, reference image I_ref, subject image I_sub
Output: Makeup image I_Imakeup
Feature point detection on I_ref and I_sub
Geometric relationship construction   (Eq.(3))
Recovered mask estimation M_ref  and M_sub   (Eq. (1))
Apply EyeDetector(x, y) on I_sub
Foreach pixel (x,y) on I_sub do
        IF (x, y) ∈ M_sub
            IF (x, y) ∈ C1
                Apply Makeup for eyebrows (Eqs. (4), (5), (6))
            ELSE IF (x, y) ∈ C2
                Apply Makeup for lip (Eqs. (7), (8), (9))
            ELSE IF (x, y) ∈ C3 or (x, y) ∈ C4 or (x, y) ∈ C5
                Apply Makeup for eyes  (Eq. (10))
            ELSE IF (x, y) ∈ C6
                Apply Makeup for skin (Eq. (11))
            ENDIF
        ELSE
            I_Imakeup (x,y) = I_sub (x,y)
        ENDIF
END
```

FIGURE 13. The proposed makeup algorithm

TABLE 1. Evaluation Database

Category	Facial Components for, Makeup Algorithm	Number of, Persons	Number of, Images
1	Eyebrow makeup	9	375
2	Lip makeup	8	170
3	Eye makeup	11	551
4	Skin makeup	7	151

open mouth and eyeglasses are rejected from our work. Table 1 lists the number of images for each facial component. Note that in the following experiments, for each category one reference image is randomly selected for each person, i.e. only one image is manually edited, and the remaining images of the same person within the same category, are automatically rendered.

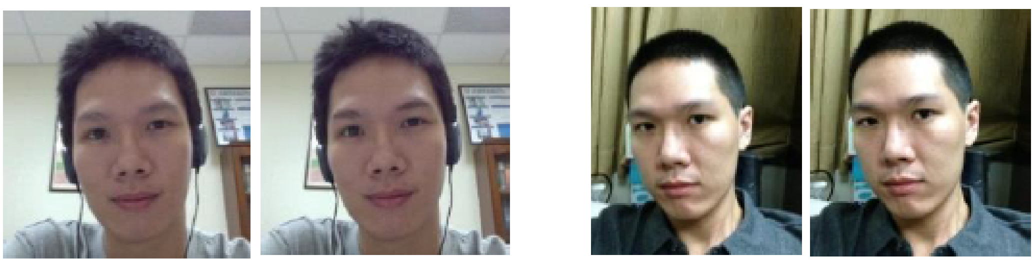

FIGURE 14. Two examples for eyebrow makeup analysis. Left of each pair: Original subject image. Right of each pair: Eyebrow makeup results.

5.1. **Analysis of Virtual Makeup Results.** The algorithms for the makeup of eyebrows and lips are similar such that they add or subtract color from the corresponding pixels of the facial components. The makeup result depends on the accuracy of the makeup region estimation. Because the global geometric relationship is created between the reference and subject images, the local non-rigid motion of the facial components would detract from the performance. Figure 14 shows an example of subject images for the makeup of eyebrows.

Figure 15. Three examples for lip makeup analysis. Left two ones are successful examples and the right one is unsatisfactory lip makeup result. Left of each pair: Original subject image. Right of each pair: Lip makeup results.

Figures 15 shows examples of the makeup for lips. Some pixels are misclassified by the makeup region on facial images with the local non-rigid motion of the mouth, such as an open mouth or a non-frontal pose with a pouty mouth, due to the limitations of the global geometric relationship. Virtual makeup for eyes primarily involves the removal of dark circles. Figure 16 shows examples of the makeup results. If the results of the detection of eyes are not precise, the pixels of eyes will be inappropriately filled with the skin color, as shown in Figure 17. Eyeglass removal, a specific issue for image inpaint, is beyond the scope of our present work. For skin smoothing, the bilateral filter is applied, and two parameters of standard deviations for the spatial and intensity Gaussian are set.

According to the results, the standard deviation for the intensity Gaussian has more influence on the makeup results. Now, when a very small standard deviation is set, the smoothing effect is not clear, whereas a very large value resultsin a blurry effect (Figure 18). Moreover, if there is a large pose difference between the reference and subject images, inconsistent results occur in which some foreground pixels are not made up, whereas some background pixels are. Figure 19 shows an example of inconsistent skin makeup in which the pixels on the left side of the face are smoothed, but the pixels on the right side are not.

6. **Conclusion.** In this paper, we proposed a framework to create a batch of face makeup by referring to one manually edited example. By face alignment, the global geometric relationship between the reference and subject images can be created, and then the makeup region on the subject image can be estimated. For obtaining a precise makeup result, the face components are further classified into six classes, and corresponding makeup algorithms are proposed to adjust the pixel color or texture information for a superior

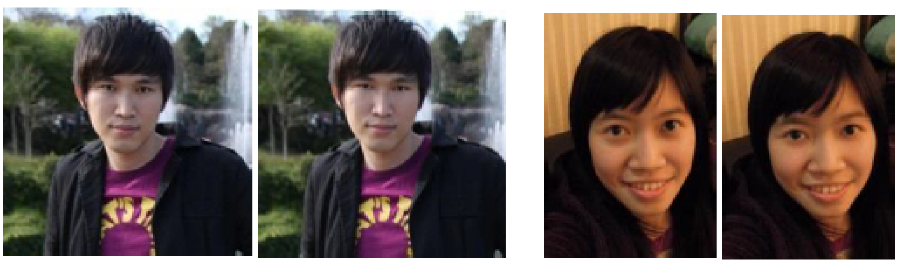

Figure 16. Two examples of the makeup for eyes to conceal dark circles. Left of each pair: Original subject image. Right of each pair: Makeup results.

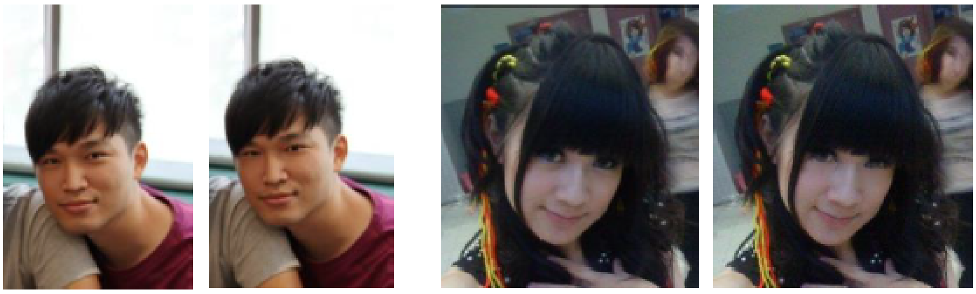

Figure 17. Unsatisfactory concealment result of the removal of dark circles. The pixels of eyes are inappropriately filled with the skin information. Left and right of each pair are the original subject images and the makeup results, respectively.

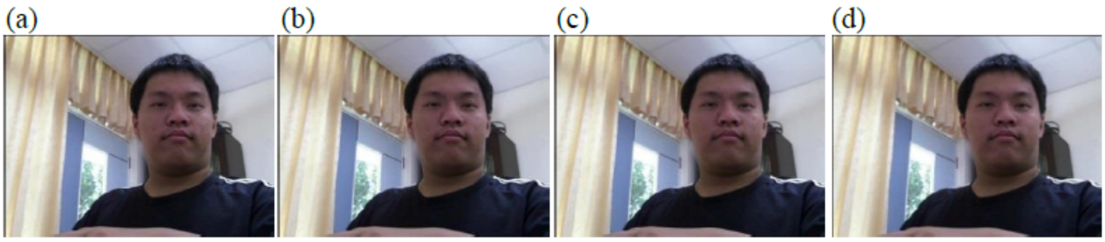

Figure 18. Example of skin makeup. (a) Original subject image (b)(d) uses the standard deviation for the spatial Gaussian of 10 and intensity Gaussian of 5, 10, and 30. A larger value of the standard deviation for the intensity Gaussian has a smoother result (c), but a very large value results in a blurry effect (d).

Figure 19. Inconsistent makeup results for skin smoothing due to large pose variation. Left: Original subject image. Right: Makeup results.

look, including increasing or decreasing the color depth of eyebrows and lips; removing of freckles, moles, and dark circles; and smoothing of skin flaws. The advantages of the proposed framework are that only one reference image is required, and the face makeup can be automatically rendered for the remaining images taken at the same duration as the reference image for the same person. The experimental results demonstrate the effectiveness of the proposed framework for facial images with flaws. In future works, to provide more satisfying makeup results, the accuracy of the feature point detection and addition of feature points will be further studied to cope with the situation of the non-frontal facial pose or non-rigid facial local motion. Moreover, the automatic detection of flaw regions will be developed to reduce manual processes.

Acknowledgment. This work is supported by National Science Council (NSC), Taiwan, under Contract of MOST 104-2221-E-151-028-. The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

REFERENCES

[1] W. S. Tong, C. K. Tang, M. S. Brown, and Y.Q. Xu, Example-based cosmetic transfer, *Pacific Conference on Computer Graphics and Applications*, pp. 211-218, 2007.

[2] ModiFace.com on URL of http://modiface.com/about.php

[3] TAAZ.com http://www.taaz.com/virtual-makeover

[4] Facetune http://www.facetuneapp.com/

[5] foror.com http://www.fotor.com/features/blemish.html

[6] ModiFace.com: http://modiface.com/about.php

[7] Perfect365 http://perfect365.arcsoft.com/

[8] Aberdeen dataset http://pics.psych.stir.ac.uk/

[9] Pixtr http://www.pixtr.me/

[10] N. Ojima, K. Yoshida, O. Osanai, and S. Akasaki, Image synthesis of cosmetic applied skin based on optical properties of foundation layers, *International Congress of Imaging Science*, pp. 467468, 2002.

[11] D. Guo and T. Sim, Digital face makeup by example, *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 73-79, 2009.

[12] A. Hertzmann, C. E. Jacobs, N. Oliver, B. Curless, and D.H. Salesin, Image analogies, *Annual Conf. on Computer graphics and interactive techniques*, pp. 327-340, 2001.

[13] N. Tsumura, N. Ojima, K. Sato, M. Shiraishi, H. Shimizu, H. Nabeshima, S. Akazaki, K. Hori, and Y. Miyake, Image based skin color and texture analysis/synthesis by extracting hemoglobin and melanin information in the skin, *ACM Transactions on Graphics*, vol. 22, no. 3, pp. 770779, 2003.

[14] K. Schebaum, T. Ritschel, M. Hullin, T. Thormahlen, V.Blanz, and H.P. Seidel, Computer-suggested facial makeup , *Computer Graphics Forum*, vol. 30, no. 2, pp. 485-492, 2011.

[15] L. Xu, Y. Du, and Y. Zhang, An automatic framework for example-based virtual makeup , *IEEE Conf. on Image Processing*, pp. 3206 - 3210, 2013.

[16] API of face++ http://cn.faceplusplus.com/

[17] M. Brand and P. Pletscher, A conditional random field for automatic photo editing , *IEEE Conf. on Computer Vision and Pattern Recognition*, pp. 1-7, 2008.

[18] T. Leyvand, D. Cohen-Or, G. Dror, and D. Lischinski, Data driven enhancement of facial attractiveness , ACM Transactions on Graphics, vol. 27, no. 3, pp. 1-9, 2008.

[19] G. Guo, Digital anti-aging in face images , *International Conference on Computer Vision*, pp. 2510-2515, 2011.

[20] C. Lee, M. T. Schramm, M. Boutin, and J. P. Allebach, An algorithm for automatic skin smoothing in digital portraits , *IEEE Conf. on Image Processing,* pp. 3149-3152, 2009.

[21] J. K. Chou, C. K. Yang, and S. D. Gong, Face-off: automatic alteration of facial features , *Multimedia Tools and Applications*, vol. 56, no. 3, pp. 569-596, 2012.

[22] C. W. Fang and J. J. Lien, Rapid image completion system using multiresolution patch-based directional and nondirectional approaches , *IEEE Trans. on Image Processing*, vol. 18, no. 12, pp. 2769-2779, 2009.

[23] N. Kawai, and N. Yokoya, Image inpainting considering symmetric patterns , *IEEE Conf. on Pattern Recognition*, pp. 2744-2747, 2012.

[24] Y.E. Loke, and R. Surendra, Image inpainting with a learned guidance vector field , *IEEE Conf. on Signal Processing*, pp. 1-5, 2009.

[25] T. Takahashi, K. Konishi, and T. Furukawa, Rank minimization approach to image inpainting using null space based alternating optimization , *IEEE Conf. on Image Processing*, pp. 1717-1720, 2012.

[26] Z. Su, X. Yang, X. Luo, and D. Wang, Local color editing using color classification and boundary inpainting , *IEEE Conf. on Pattern Recognition*, pp. 3196-3199, 2012.

[27] L. Yin, X. Song, and H. Jiang, An inpainting method for face images , IEEE Conf. on Communication Technology, pp. 393-396, 2011.

[28] C. Wu, C. Liu, H. Y. Shum, Y. Q. Xu, and Z. Zhang, Automatic eyeglasses removal from face images, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 26, no. 3, pp. 322-336, 2004.

[29] M. Everingham, J. Sivic, and A. Zisserman, Hello! my name is... Buffy–automatic naming of characters in TV video , *British Machine Vision Conference*, pp. 899-908, 2006.

[30] T.S . Cho, W. T. Freeman, Facial skin beautification using region-aware mask , *International Conference on System, Man, and Cybernetics*, pp. 2922-2926, 2013.

[31] L. Liang and L. Jin, A reliable skin mole localization scheme , *International Conference on Computer Vision*, pp. 1-8, 2007.

[32] T. F. Cootes, D. Cooper, C. J. Taylor, and J. Graham, Active shape models-their training and application, *Computer Vision and Image Understanding*, vol. 61, no. 1, pp. 38-59, 1995.

[33] T.F. Cootes, G.J. Edwards, and C.J. Talor, Active appearance models , *IEEE Trans. on pattern analysis and machine intelligence*, vol. 23, no. 6, pp. 681-685, 2001.

[34] C. T. Tu and J. J. Lien, Automatic location of facial feature points and synthesis of facial sketches using direct combined model , *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 40, no. 4, pp. 1158-1169, 2010.

[35] Z. Farbman, R. Fattal, D. Lischinski, and R. Szeliski, Edge preserving decompositions for multi-scale tone and detail manipulation , *ACM Transactions on Graphics*, vol. 27, no. 3, pp. 1-10, 2008.

[36] C. Tomasi and R. Manduchi, Bilateral filtering for gray and color images , *International Conference on Computer Vision*, pp. 839 - 846, 1998.