Facial Makeup Transfer Combining Illumination Transfer

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ABSTRACT To meet the women appearance needs, we present a novel virtual experience approach of facial makeup transfer, developed into windows platform application software. The makeup effects could present on the user’s input image in real time, with an only single reference image. The input image and reference image are divided into three layers by facial feature points landmarked: facial structure layer, facial color layer, and facial detail layer. Except for the above layers are processed by different algorithms to generate output image, we also add illumination transfer, so that the illumination effect of the reference image is automatically transferred to the input image. Our approach has the following three advantages: (1) Black or dark and white facial makeup could be effectively transferred by introducing illumination transfer; (2) Efficiently transfer facial makeup within seconds compared to those methods based on deep learning frameworks; (3) Reference images with the air-bangs could transfer makeup perfectly.

INDEX TERMS Facial Makeup Transfer , Single Reference Image , Illumination Transfer , Facial Parsing , Efficient and Effective.

I. INTRODUCTION

FACEIAL makeup transfer is a new application requirement of virtual reality technology in the image. How to see the virtual makeup effect on the image is the need of many young women. Facial makeup is a technique that changes the appearance with special toiletries such as compact, setting powder, and moisturizer. Under many circumstances, particularly for females, makeup is deemed as a necessary practice to beautify appearance. Emulsions are often used to alter the facial skin detail. Compacts are primarily used to hide defects and overlay the initial facial skin detail. Setting powder often satisfies detail for the skin. Except that, other colour makeup, such as eyeliner and shadow, is applied to the upper layer of the setting powder.

The ever-developing makeup technology now extends to different women facial types, different scenes, different ages, different skin, and even different costumes with different makeup [15]–[33]. The choice of makeup naturally creates a personal experience but greatly consumes time and damages women’s skin.

Our method based on the technical application of facial makeup transfer completely considered all of the above circumstances. As shown in FIGURE 1a, with the image prototype (FIGURE 1a) as the input image, with the pattern example (FIGURE 1b) as the reference image, our method could successfully transfer the reference image makeup to the input image to generate output image (FIGURE 1c).

II. RELATED WORK

In 2007, Tong et al. [1] of the Hong Kong University proposed a facial-to-facial makeup transfer method based on a quotient image. Using the quotient image from a pair of images of the identical person applying and removing makeup as reference images to transfer the reference makeup to the input facial image. Their presented method could be divided into four steps, firstly removing the eyebrows and eyelashes of the input image to prepare for the eye makeup transfer. Then filling resulting holes using texture-synthesis, thus to extract inherent skin features of the input image. Manually specifying the point correspondence between the facial image and the facial model containing 84 landmark points to prepare for facial deformation. Secondly, the reference facial image is deformed according to the input image. Their presented method could be divided into four steps, firstly removing the eyebrows and eyelashes of the input image to prepare for the eye makeup transfer. Then filling resulting holes using texture-synthesis, thus to extract inherent skin features of the input image. Manually specifying the point correspondence between the facial image and the facial model containing 84 landmark points to prepare for facial deformation. Secondly, the reference facial image is deformed according to the input image. Thirdly, the output is multiplied by the input image to achieve the makeup transfer, where the makeup of the same facial before and after is used to indicate the change of the makeup. Finally, eye makeup requires additional processing, which is generally more complicated, and the color is changeable.
In 2009, Guo et al. [2] of the Singapore National University proposed a simpler method, not for reference image before facial makeup but for an reference image after facial makeup. The method first performs facial alignment between the input facial image and the reference facial image. Since the information is transferred from pixel to pixel, it needs to be fully aligned before transferring, and then layer is decomposed by the Edge Preserving Smooth Filter. The input image and the reference image are resolved into the following three layers: facial structure layer, facial color layer, and facial detail layer. The information for each layer of the reference image is transferred to the homologous layer of the input image differently: the facial detail layer is direct transferred; the facial color layer is transferred in alpha hybrid mode. The three composite layers are combined to obtain the resulting image.

In 2015, Li et al. [3] of Zhejiang University proposed a facial image makeup editing method based on intrinsic images. The method uses the intrinsic image decomposition method to directly decompose the input facial image into the illumination layer and the reflectance layer, and then edits the makeup information of the facial image in the reflectivity layer, rather than need reference image, and finally decomposes the previous image. The illumination and shadow layers are combined to obtain a makeup editing effect.

In 2016, Liu et al. [4] of NVIDIA Research designed a new deep convolutional neural network for makeup transfer, which not only could transfer makeup, eye shadow, lip makeup, but also recommend the most suitable input image's makeup. The network consists of two consecutive layers are combined to obtain a makeup editing effect. The main idea is to train the generation network $G$ and the authentication network $A$ to transfer a specific makeup style. Chang et al. [5] trained three generators separately, focusing the network capacity and resolution on the unique features of each region. For each pair of images before and after makeup, firstly apply a facial analysis algorithm to segment each facial component, such as eyes, eyebrows, lips, nose, and etc. Finally each component is separately calculated and recombined.

III. FACIAL MAKEUP TRANSFER

Our method uses the input image $I$ which applies facial makeup image and the reference image $R$ which provides the makeup example style as input, and the result is the output image $O$ which retains the facial structure of $I$ while applying the makeup style from $R$. The notation we used is enumerated in TABLE 1.

The complete pipeline is shown in FIGURE 2. Before the pipeline begins, we need to perform whitening and smoothing pretreatment onto the input image as a small optimization. The pipeline mainly has the following four steps. Firstly, facial alignment has to be done between the input facial image and the reference facial image. Since the information is transferred from pixel to pixel, it needs to be perfectly aligned before the makeup transfer. We use a modified Active Structure Search Algorithm to find the corresponding 90 feature points and affine transformation to distort the reference image $R$ into the input image $I$. Secondly, followed by layer decomposition. Both $I$ and $R$ are resolved into the following three layers: facial structure layer, facial color layer, and facial detail layer. Thirdly, the information from per layer of $R$ is transferred to the related layer of $I$ in their own way: facial detail is transferred directly; facial color is transferred through alpha blending; facial illumination of the facial structure layer is transferred with specific algorithm. And three composite layers are ultimate combined. Fourthly, we use facial parsing to judge facial label probability of each pixel and then retain the components of the input image and the components of the initial makeup in different probability.
to fuse into the final makeup.

### A. WHITENING AND SMOOTHING

On the one hand, we use the OpenCV Color Balance Algorithm to achieve facial whitening. Color balance global adjustments image dominant colors including red, green and blue. The whole process is briefly described below: firstly initializing image each pixel brightness area (i.e. highlights, mid-tones, shadows), nextly adjusting each brightness area corresponding variable parameters with color balance coefficient, then figuring out image red, green, blue channel value used for adjusting image color, finally balancing the whole image color based on red, green, blue channel value. On the other hand, we use the OpenCV Bilateral Filtering Algorithm \([12]\) to achieve facial smoothing. Bilateral filtering performed in the CIELAB color space is the most natural type of filtering for color images: only perceptually similar colors are averaged together, and only perceptually important edges are preserved while eliminating noise. The basic idea underlying bilateral filtering is not only considers the influence of the position on the central pixel, but also considers the similarity degree between the pixel and the central pixel in the convolution kernel, and generates two different weights according to the similarity degree between the position influence and the pixel value. Consider the two weights when computing center pixels, and realize bilateral low-pass filtering.

### B. FACIAL ALIGNMENT

For facial alignment, we firstly use the modified Active Shape Model (ASM) of Milborrow et al. \([14]\) to obtain the facial feature points and then use the affine transformation algorithm to warp the reference image \(R\) into the input image \(I\). Due to the variety of appearances in the underside of various possible makeup, our facial feature points landmark software needs to obtain more precise facial feature points in an automatic and manual manner. Our examples of a total of 90 landmark points on the facial are shown in FIGURE 3.

### C. LAYER DECOMPOSITION

The facial is segmented according to the components distribution of each pixel. As shown in FIGURE 4 we utilize facial parsing of Liu et al. \([6]\) to define different facial components to obtain components label of per pixel, including hair, eyebrows, eyes, nose, lips, mouth, facial skin and background.

As shown in FIGURE 5 we use the above 90 landmark feature points including the input image and reference image to warp the reference image \(R\) to input image \(I\) for facial alignment.

We parse the input facial image and select 11 sorts of labels which seldom cover all the facial components. Then we tint 11 facial component labels to get the facial hard mask. Next we segment facial into different regions with facial hard mask, guiding different makeup transfer operations onto facial regions.

We choose CIELAB color space to decompose the input image \(I\) and the reference image \(R\) (after warping) into facial structure layer, facial color layer (i.e. CIELAB color channels \(a\), \(b\) channel), and facial detail layer. The CIELAB color space of Lukac et al. \([7]\) performs better than other color spaces in terms of separation brightness and approximates the perceptual unity of Wood-land et al. \([8]\).

Secondly, according to the approach of Eisemann et al. \([9]\), Zhang et al. \([10]\), and the Weighted Least Squares (WLS) presented by Farbman et al. \([1]\), we perform edge-preserving smoothing filter on the luminance layer \(L\) to extract the facial structure layer \(s\), then subtracted from the luminosity layer \(L\) to obtain a facial detail layer \(d\).

### D. LAYER TRANSFER

We define the facial detail layer \(O_d\), i.e.

\[
O_d = R_d
\]  

We define the facial color layer \(O_{a, b}\) as the alpha-blending of the CIELAB color channels \(a\) and \(b\) of \(I\) and \(R\), i.e.

\[
O_{a, b}(p) = (1 - \alpha)I_{a, b}(p) + \alpha R_{a, b}(p), \& p \in C_1
\]  

where \(\alpha = 0.95\) is the mixing weight that controls the two color channels, \(p\) is the image pixel point, \(C_1\) is the skin region of the facial image, and \(\& p \in C_1\) means the image pixel point belonging to facial skin region.

We define the facial structure of \(O_s\) as

\[
O_s = R_s
\]  

| Notation | Meaning |
|----------|---------|
| \(I\) | Input image |
| \(R\) | Reference image (after warping) |
| \(O\) | Output image |
| \(I_s\) | \(\{\}\) Facial structure layer |
| \(I_d\) | \(\{\}\) Facial detail layer |
| \(I_{a}\) | \(\{\}\) CIELAB facial color layer a |
| \(I_{b}\) | \(\{\}\) CIELAB facial color layer b |
| \(\alpha\) | Weight controlling the degree of blending \(R_{a, b}\) and \(I_{a, b}\) in \(O_{a, b}\) |
| \(\beta\) | Weight controlling the illumination transfer \(R_s\) and \(I_s\) in \(O_s\) |
| \(p\) | Image pixel point |
| \(C_1\) | Skin region of the facial image |
FIGURE 2: The pipeline of facial makeup transfer. Our method is divided into five steps: whitening and smoothing, facial alignment, layer decomposition, layer transfer and illumination transfer.

E. ILLUMINATION TRANSFER

We define the following formula to achieve illumination transfer:

\[
O_s(p) = \begin{cases} 
\frac{I_s(p) - (I_s(p) - R_s(p)^2)}{\beta}, & \text{if } I_s(p) > R_s(p) \\
I_s(p), & \text{otherwise}
\end{cases}, \quad p \in \mathcal{C}_1
\]

where \( \beta = 30 \) as the illumination transfer parameter between input facial structure and reference facial structure, \( p \) is the image pixel point, \( \mathcal{C}_1 \) is the skin region of the facial image, and \( \&p \in \mathcal{C}_1 \) refers to the image pixel point belonging to the facial skin region.

IV. EXPERIMENTS AND RESULTS

A. DATA COLLECTION

For our makeup transfer experiments, in order to achieve better results, we collect two separate high-resolution datasets, one containing before-makeup faces with nude makeup or very light makeup and another one containing faces with a large variety of facial makeup styles. To this end, we collect...
B. EFFICIENT MAKEUP TRANSFER

Comparison results between us and Guo et al. [2] are shown in FIGURE 7. On the one hand, Guo et al. [2] method assume the illumination in the reference image is uniform, but it is not necessary to be the same as the input image. If any shadow or specularity exists, they would also be transferred to the input image. To solve this problem, we introduce illumination transfer to detect and remove shadow or specularity; our results are shown in FIGURE 7.

On the other hand, Guo et al. [2] method does not work well for black and dark makeup. In their result, the dark regions appears gray and unnatural. The black color is the foundation in physical makeup; but their method only transfers the detail introduced by foundation. The black color is interpreted as no color in CIELAB color space; the illumination 

our own datasets from major websites. We manually identify whether each facial image is indeed a before-makeup or with-makeup face with eyes open and without occlusions. By this way, we harvest a before-makeup dataset of 526 images and a with-make up dataset of 878 images. Our datasets contain a wide variety of facial makeup styles.
FIGURE 6: To make makeup transfer further achieve better result, we whiten and smooth facial skin component. Then facial components are further divided into three classes, yellow for facial skin as $C_1$; green for eyes and mouth cavity as $C_2$; and the rest of the black part is not considered. Moreover, then the facial part $C_1$ and $C_2$ would perform different makeup task.

FIGURE 7: Comparison results between us and Guo et al. [2], Neural Style makeup transfer examples [13], and Liu et al. [4]. The foundation is uniformly dark, which is not transferred faithfully in Guo et al. [2] In our result, black or dark makeup appears natural.
of black color is especially important to human perception. But the illumination is not transferred in their method. Thus, the dark color in their result appears gray. We solve the problem through the way that adding illumination transfer with user control coefficient in the degree of illumination transfer, and our results are shown in FIGURE[7].

**C. EFFECTIVE MAKEUP TRANSFER**

Comparison results between us and Chang et al. [5], as shown in FIGURE[8]. As we have compared in the above results, the method of the Chang et al. [5] could only transfer the makeup of the eyes and lips, whereas could not transfer the makeup of the skin part, but our method is not only transfer the eyes and lips makeup, but also transfer the skin part makeup, which is equivalent to a combination of both. Except that, their method for fine hair could not be effectively treated, but our method could overcome it.

Other comparison results between us and Liu et al. [4]. As shown in FIGURE[7], our makeup result works better than Liu et al. [4] method. As we could see, our method could transfer facial skin detail of the reference image, thus conduct to form new detail, while Liu et al. [4] method could not do that. Furthermore, our method that combine makeup and relighting could handle the reference image with eye black and dark makeup rather than Liu et al. [4].

Last but not least important, the time and space complexity of our method is lower than Liu et al. [4]. As shown in TABLE[2] the running time for beautyf makeup is within 2 seconds on an iPhone6 for a pair of 224 × 224 color image with our method. For Liu et al. IJCAI 2016 [4], it needs to take 6 seconds on a TITAN X GPU for a pair of 224 × 224 color image.

**D. AIR-BANGS MAKEUP TRANSFER**

So far, there is still no good way to deal with makeup transfer with reference examples of air-bangs in the traditional computer vision fields and deep learning fields. Since these methods rely on extremely accurate facial feature landmark without any exception, so as to generate a natural facial mask. As for the reference examples in real life are very diverse, these methods could not make hair and skin very naturally segregate, resulting in the problem that the hair of the reference examples is also transferred together. In order to solve such a tough circumstance, we have further improved our method above, successfully solving the problem of hair and skin boundary in makeup transfer, as shown in FIGURE[9].

The main process as follow, firstly we conduct facial whitening and smoothing and use facial parsing of Liu et al. [6] to acquire the hard mask of the input image with air-bangs, then we utilize the previous method to generate the initial makeup, in which process we could notice that the hair makeup of the reference image also transfer to the input image unexpected. Followed, we need to convert the hard mask into soft mask which could judge the facial components in terms of probability. Combined the soft mask of the input image, we could make the input image preserve four facial components: eyes, mouth, air-bangs, and the background parts. At the same time, we make the initial makeup preserve four facial components: skin, eyebrows, nose, and lips parts. Thirdly, we fuse the pixels of the input image’s facial retention component and the initial makeup result’s facial retention component with different probabilities. Finally, we combine the above fusion results to generate the final makeup.

**E. QUANTITATIVE COMPARISON**

The quantitative comparison mainly focuses on the quality of makeup transfer and the degree of harmony. On the one hand, we conduct 100 makeup transfer experiments and compare our results with Guo et al. [2], Neural Style [13], and Liu et al. [4]. Each time, a 7-tuple, i.e., a input facial mages, a reference facial image, the result facial images by our method and above methods, are sent to 20 participants to compare. Note that the four result facial images are shown in random order. The participants rate the results into five degrees: better, better, same, worse, and worse. The percentages of each degree are shown in TABLE[8]. Our method is much better than Guo in 23.6% cases. We are much better than NerualStyle-CC and NerualStyle-CS in 90.1% and 92.3% cases. And We are much better than Liu in 32.9% cases.

On the other hand, we conduct a user study on Amazon Mechanical Turk making a pairwise comparison among results of the method of Chang et al. [5] and of our method. We randomly select 102 input facial mages and reference facial image, so we have 102 groups of makeup transfer results to compare. Then we ask 10 or more subjects to select which result better matches the makeup style in the reference. On average 87.3% of people prefer our results over those of Chang et al.

**V. CONCLUSION**

In this paper, we propose a novel makeup transfer method that adapts to most of sample images. The main innovations are as follows: firstly, in the makeup transfer process, we conduct the illumination transfer in the facial structure with our special algorithm; secondly, we expand the makeup to air-bangs circumstances. The major advantages of our method are efficient, effective, and could handle the reference image with air-bangs. Since the reference images only require skin detail and color information to beautify the appearance, the facial structure of input image is no longer needed, helping to protect the privacy of the makeup actor. We apply the latest and most fashionable makeup examples to our system so that users could apply virtual makeup to their faces in real time according to individual needs, just like a tailor-made personal beauty salon.

As we dilate above, our approach has the following three advantages:
FIGURE 8: Comparison results between us and Chang et al. [5].

TABLE 2: Runtime Comparison.

| Methods            | Environment                                      | Time  |
|--------------------|--------------------------------------------------|-------|
| Liu et al. IJCAI 2016 [4] | 224 × 224 image pair using TITAN X GPU | 6s    |
| Our method         | 224 × 224 image pair using iPhone6              | 2s    |

TABLE 3: Quantitative comparisons between our method and four other makeup transfer methods. Each percentage in the table means our method is much better (or better, same, worse, much worse) than Guo, NerualStyle-CC, NerualStyle-CS, and Liu in percentage cases.

| Methods            | much better | better | same | worse | much worse |
|--------------------|-------------|--------|------|-------|------------|
| Guo et al. [2]     | 23.6%       | 66.7%  | 25.2%| 10.2% | 0.93%      |
| NerualStyle-CC [13] | 90.1%       | 16.2%  | 3.13%| 0.13% | 0%         |
| NerualStyle-CS [13] | 92.3%       | 16.8%  | 1.98%| 0.21% | 0%         |
| Liu et al. [4]     | 32.9%       | 28.4%  | 5.13%| 0.33% | 0.14%      |
(1) Black or dark and white makeup could be effectively transferred by introducing illumination transfer;
(2) Efficiently transfer makeup within seconds compared to those makeup methods based on deep learning framework;
(3) Examples with the air-bangs could make makeup transfer perfectly.

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