Example-Based Cosmetic Transfer

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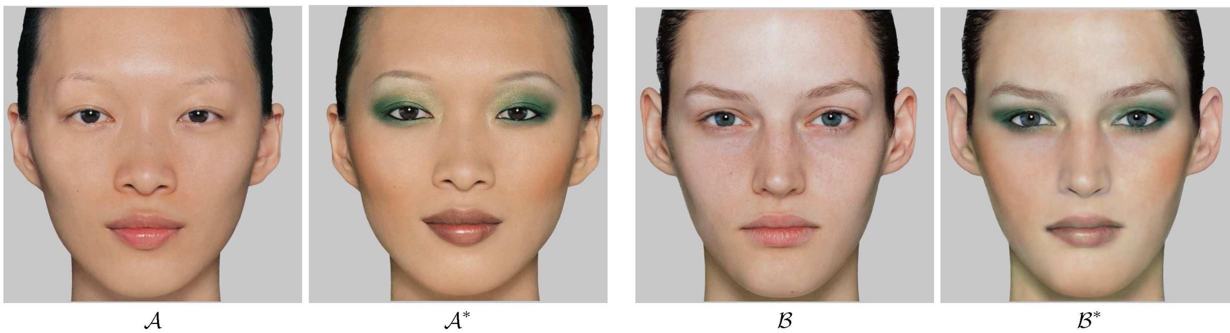

Figure 1: Example-based cosmetic transfer. A and A^* are the "before-and-after" makeup images of an Asian woman. B is an image of a woman of European descent. B^* is our result, after transferring the cosmetic style depicted in A^*. Only the cosmetic style is transferred. Skin tone and personal features such as eyebrows and eyelashes in B are preserved after the transfer.

Abstract

Cosmetic makeup is used worldwide as a means to enhance beauty and express moods. An art form in its own right, cosmetic styles continuously change and evolve to reflect cultural and societal trends. While countless magazines and books are dedicated to demonstrating cosmetic art, the actual application of makeup still remains a physical endeavor.

In this paper, we describe a procedure to apply cosmetic makeup to the image of a person's face with the click of a mouse. Our approach works from before-and-after example images created by professional makeup artists. Using our "cosmetic-transfer" procedure, we can realistically transfer the cosmetic style captured in the example-pair to another person's face. This greatly reduces the time and effort needed to demonstrate a cosmetic style on a new person's face. In addition, our approach can be used to mix-and-match, and even fine-tune, example styles, all virtually, without the need for any physical makeup.

Keywords: image-based rendering, cosmetic-art, applications.

1. Introduction and Motivation

Professional application of cosmetic makeup is an art form all to its own. Particularly unique to this art form is its canvas, the human face – a canvas whose innate familiarity embodies that which it is to be human. While powder, lipstick, eye-liner, and eye-shadow are some of the many tools employed in cosmetic art, the success of their application comes from the intuition and experience of the makeup artist in identifying and attenuating an individual face's subtle features to highlight and often enhance a person's natural beauty.

Interestingly, it is this human canvas that offers another unique dimension to cosmetic art, that of evaluation. Because the underlying form of the face is so singularly familiar to the observer, subjective evaluation can be easily obtained by observing the effects of cosmetic art as revealed in before and after images. Not surprisingly, before-and-after image pairs are an accepted approach for makeup artists to demonstrate their skills and individual styles. An example is shown in Figure 1. In this particular example, care has been taken to ensure that the underlying face has been imaged under the same position and lighting. We refer to these images as A and A^*.

While these image pairs serve their purpose and allow a subjective evaluation of the makeup styles, it is the nature of the familiar canvas that leads to the most obvious question of the observer – "How would this look on me?". Diversity from facial geometry, skin tone, skin texture, hair color, and hair density, however, make its sufficiently difficult to envision how the same style might appear when applied to another person's face (denoted as *B*). Currently, the only solution is a physical one, involving applying the makeup in the same or similar fashion to see the affect.

The ability for an observer to digitally apply makeup styles demonstrated in before-and-after images to a photograph of their own face is an innovation that would undoubtedly be widely accepted. While we note that cosmetic art is inherently customized to the facial geometry, skin tone, and unique features of the individual in the example, it is difficult to deny that a point-and-click interface for transferring the cosmetic styles captured in a database of example-pair images on to a different face (presumably the observer) would not be of significant use. To this end, we propose such a system using what we refer to as "example-based cosmetic transfer".

[Contribution] We propose an image-based technique to achieve this desired cosmetic transfer by example. Given a database of before-and-after makeup image pairs, our goal is to transfer a cosmetic style onto a new target face (*B*) as shown in Figure 1. Central to this cosmetic transfer problem is the mapping of cosmetic contributions of color and subtle surface geometry, at least in appearance, from the example image pairs to a new and different target face.

To address this problem many issues must be considered. While we want to transfer cosmetic style, inherent skin features on the example face, such as freckles, moles, and blemishes should not be transferred. Inherent skin features on the target face, however, should be preserved (at various extents) after makeup application, especially for a subtle makeup style. Differences in the skin tone and facial hair color (i.e., eyebrows) must be addressed to produce realistic results. In an application context, the ability to digitally transfer cosmetics by example allows the user the flexibility to control the amount of makeup applied, producing examples of heavy versus light makeup application and even the possibility to combine different cosmetic styles. Considering the issues and challenges stated above, our overall approach consists of 1) computing the changes in color and illumination before and after makeup, 2) accommodating different skin texture and tone between the example and target faces, and 3) rapidly applying and adjusting the makeup style to a given target face.

2. Related Work

Cosmetic Makeup There is not a great deal of previous work addressing the transfer of cosmetic styles. The closest related work to ours by Ojima et al. [17] examined how to transfer the effects of *foundation* using before-and-after images. While similar, this work limited itself to cosmetic foundation, which is applied to make the skin look uniform and smooth and is typically only the first step in makeup application. Subsequent makeup was not addressed. There are several "virtual makeup" software (e.g. *Makeover* [14]) where the user can load a face image and manually apply various types of makeup using an interactive interface. Currently, such software is no more than specialized paint programs and their results are not very convincing.

Face modeling and reflectance Other work related to facial cosmetic is that focused on acquiring and modeling the reflectance of skin/face for subsequent rendering. Marschner et al. [15] acquired the bidirectional distribution function (BRDF) of facial skin from range and color images by assuming the BRDF is homogeneous over the whole face. More recent work by Debevec et al. [6] acquired a thorough BRDF model of the face for use in rendering. Pioneering work in modeling skin reflectance was proposed by Hanrahan and Krueger [9]. Later work by Jensen at al. showed how subsurface light transport properties can also be used to aid the realistic rendering of makeup blended on top of skin [11]. Besides the acquisition and modeling of skin reflectance of humans, another research direction focuses on image-based approaches for face rendering. Marschner and Greenberg [15] proposed an inverse lighting method that estimates the lighting condition casting on, say a human face, using a set of basis images. Riklin-Raviv and Shashua [19] provided a similar approach that could also transfer shading from examples based on color ratio, or what they termed the *quotient image*.

Image analogy Example-based cosmetic transfer is inspired by Hertzmann et al.'s image analogy [10]. Unlike our work, however, the non-photorealistic nature of image analogy does not require strong semantic information. To be realistic, our cosmetic transfer needs to impose constraints pertinent to faces, i.e. facial structures must be preserved. The cosmetic transfer may not be applied equally to all pixels on the target face, because certain cosmetics may reduce the effect of inherent skin features. Such features need to be separated during pre-processing and re-applied with different extents, depending on the makeup style.

Expression ratio image and cosmetic transfer Our example-based cosmetic transfer (section 3.2) is somewhat similar to the use of ratio image proposed by Liu et al. [13] for expression cloning, but differs in the following aspects: while expression cloning using ratio images registers geometry changes due to expression, our cosmetic transfer encodes color and reflectance change due to cosmetics, where geometry is assumed to be invariant after warping all faces (to the canonical face). Moreover, our Laplacian transfer operator (section 3.3) is necessary to correct the appearance (e.g. smooth or rough) introduced by subtle geometry or texture changes due to the applied makeup.

3. Cosmetic Transfer

To achieve the desired cosmetic transfer from before-and-after images we have developed an approach that uses the following four steps: 1) pre-processing, 2) cosmetic mapping, 3) appearance correction, and 4) eye transfer. These are described in the following.

3.1. Pre-Processing

In all the examples in this paper, the three images A, A^*, and B have been carefully acquired under similar illumination and pose.

This is not uncommon for before-and-after image capture used in cosmetic makeup books. To synthesize B^*, we first pre-process the images to 1) remove the eyebrows and eyelashes, 2) fill-in the resulting holes using texture-synthesis, 3) extract inherent skin features, and 4) warp the facial geometry to a canonical face model.

Eyes Eyes are the most complex features on our face, and we propose to apply facial cosmetics first, and treat the eyes separately. As a result, the eyes need to be segmented out before computing the cosmetic transfer. Since eyebrows and eyelashes are hairs and soft objects, we use Bayesian matting proposed by Chuang et al. [3] to perform eyebrows and eyelashes segmentation. This is not a difficult procedure and can be quickly performed using a quick specification of a tri-map, where the background, foreground, and uncertain region are roughly marked. The matting in the uncertain region is performed automatically using the technique outlined in [3]. The output is an alpha mask, α, the represents the contribution of eyebrows and eyelashes from the input image B, as show in Figure 2.

(a) (b) (c)

Figure 2: Eyebrows and eyelashes segmentation: image is enlarged for visualization. Top: (a) The original eye. (b) The alpha matte, α, of eyebrows and eyelashes output by Bayesian matting. (c) Repaired result.

Hole Repair The holes that results after eyebrows and eyelashes are segmented from the original image are repaired to fill in the missing pixels. There are a host of techniques to achieve this image repair with acceptable results, including image inpainting [2] and texture-synthesis [8; 12]. Our implementation is based on the graph-cut texture-synthesis algorithm proposed by Kwatra et al. [12] and uses the imagery surrounding the hole as texture patches. Figure 2(c) shows the result of repairing the resulting holes after eyebrows and eyelashes segmentation. We note that current commercial software such as Digital Image Pro 10.0 [7] now provide such hole repair functionality with very impressive results.

Skin Inherent skin features, such as freckles, moles, and blemishes, should be removed from all face images A, A^*, B before computing the cosmetic transfer, since they are not part the actual makeup and should not contribute to the transfer function. A skin patch is first chosen from a face image. Typically, the sampled patch should contain moles, freckles, and example blemishes (if present). Independent component analysis (ICA) proposed Tsumura et al. [21] by is applied to the patch, in order to obtain the separation matrix for the two skin pigments, melanin and hemoglobin, that account for certain visible spots on human skin .

For subtle makeup style, we do not discard the colors separated out by ICA. Instead, the colors due to melanin pigments are usually thresholded to digitally reduce their visibility, this often makes the face in the image look whiter with a more uniform skin tone.

Canonical Face Warp Starting from the pre-processed images, all images are warped to a canonical face space. This ensures that processing from all images can be transformed to any other image via the canonical face. This is currently performed by manually specifying 2D point correspondences between the input image and a canonical face model. This is undoubtedly the most time consuming portion of our application. Techniques such as Active Appearance Models [4] that are trained specifically for faces could be used to reduce this manual processing.

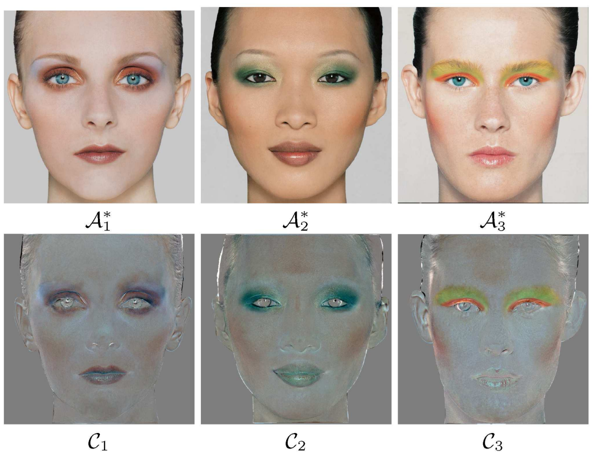

Figure 3: The computed cosmetic map, C_i, for the three different example makeup styles A^*_i, $i = 1, 2, 3$. The pixel values have been offset by +127 for better display.

3.2. Cosmetic Mapping

The cosmetic transfer is computed in a pixel-wise fashion from the three warped images, which now have the same 2D geometry. The cosmetic transfer encodes the change in color and reflectance (or BRDF) due to cosmetics in a pixel-wise manner after makeup.

Using the intrinsic image representation [1] and the Lambertian assumption, an image can be modeled as pixelwise product of two intrinsic images, one encoding the reflectance and the other encoding the illumination. Under the same illumination and given the same face A, the change due to the applied cosmetic can be modeled by $c_p = a^*_p / a_p$ where a_p and a^*_p are the respective intensity of the pixel p before and after makeup. The cosmetic map C is given by the collection of all c_ps in the image. Figure 3 shows the cosmetic transfer for a typical makeup style. Pixel values are offset by 127 for display purpose.

After computing the cosmetic map, we apply it onto the target face B in a pixelwise fashion: $b^*_p = c_p b_p$. Note that the inherent skin features we extracted from B are blended with the image produced by this transfer equation. The more subtle the makeup is, the more visible these skin features in the final makeup image. The output B^* is therefore the collection of all $\{b^*_p\}$.

3.3. Appearance correction

The color at each pixel p is synthesized by:

$$b^*_p = b_p (\gamma (c_p - 1) + 1) \tag{1}$$

where $b_p \in B$ and $c_p \in C$ are the colors of the target face and the cosmetic map, and b^*_p is the synthesized color at pixel p, respectively. $\gamma \in [0, 1]$ controls how much the cosmetic is applied: when $\gamma = 1$, Equation (1) reduces to the transfer equation $b^*_p = c_p b_p$; when $\gamma = 0$, Equation (1) becomes $b^*_p = b_p$, i.e., no makeup is applied. Note that the scalar multiplication in Equation (1) is pixelwise, i.e., is multiplied with $c_p - 1$ at each pixel p.

We note that pure color transfer is sufficient for digital makeup only when the example and target faces have equivalent geometry and reflectance, and perfect facial correspondences are available. Both conditions are very difficult if not possible to achieve in practice. The computed cosmetic map C only accounts for color and reflectance changes. Difference in appearance caused by subtle geometry change caused by the applied makeup is not explicitly captured by C.

To correct the appearance introduced by this subtle geometry change, we consider the Laplacian of the example makeup image, and map this second-order information to the output image. We make the following assumption in our image-based approach, which is applicable to a wide range of face cosmetics: the appearance change due to local geometry variation can be sufficiently captured by the Laplacian operator which computes its difference from neighboring pixels. Using this assumption, subtle changes in geometry due to makeup can be approximated by blending a^*_p and b_p at each pixel p. The local Laplacian is estimated by the following equation:

$$\Delta(b^*_p) = \Delta(\beta\, b_p + (1 - \beta)\, a^*_p) \tag{2}$$

where $\Delta(\cdot)$ denotes the Laplacian operator, and β determines the relative amount of local geometry to be transferred from b_p and a^*_p.

Assuming β is defined by the user, all terms on the right hand side of the above equation are fixed. Thus, we need to modify the image pixels b^*_p such that $\Delta(b^*_p)$

is satisfied. This can be performed using an iterative Gauss-Seidel solver, where $\Delta(b^*_p)$ from Equation (2) is fixed, and b^*_p from Equation (1) is iteratively optimized to produce the final pixel color to satisfy the Laplacian computed in Equation (2).

$\mathcal{B}_1^*$ $\mathcal{B}_2^*$ $\mathcal{B}_3^*$

Figure 4: Final results, applying our cosmetic transfer and appearance correction using Laplacian transfer, and compositing the eyebrows and eyelashes on the target face.

3.4 Eye Transfer

Drastic makeup effects of eyelashes and eyebrows should be handled by more sophisticated models (involving modeling hair length, color, and density), which is a topic in itself for further investigation. We achieve convincing results by transferring the segmented eye-brows and eyelashes to B^*. This can be done by simply adding the eye-brows and eyelashes from B to B^* using the extracted alpha mask, α.

Figure 4 show the three styles after cosmetic mapping, correction by the Laplacian operator, and compositing the eyebrows and eyelashes onto the makeup face.

4. Results and Applications

A large number of different makeup styles were transferred onto a target face using our system. In many cases, the facial geometry of the example face and the target face are very different. They also have very different skin tones, skin textures, hair color and density. In all cases, only the cosmetic style, but not the inherent features nor the skin tone/color of the example face, is transferred. Overall, the results are very convincing.

The amount of makeup is adjustable in our system. Figure 5 shows a heavy versus a light makeup of the same style. In Figure 6, we show the results on the same style whose subtle appearance is different: we provide an option to the user to transfer different extents of subtle geometry due to the makeup from the example face, using the Laplacian operator introduced in the previous section. Inherent skin features to be excluded or preserved in cosmetic transfer is an issue. Figure 7 shows inherent skin features (freckles or pimples) of one portion of the example face. They are not transferred to the target face after makeup.

Heavy $\mathcal{B}'_3$ Light $\mathcal{B}'_3$

Figure 5: The user can adjust the amount of makeup by adjusting the parameter γ that controls coverage as described in Equation (1).

more texture less texture

Figure 6: The user can adjust the amount of texture introduced by changes due to subtle geometry of the applied cosmetic.

$\mathcal{A}_4^*$ $\mathcal{B}_4^*$

Figure 7: Freckles and moles in the example makeup image A^*_4 are not transferred to B^*_4 .

Of course, image touch up can be performed on the output results. For example a brush, implemented using the method proposed by Perez et al. [18], can be used to re-touch the output makeup image in case of small visual artifacts that results when misalignment and unmatched face geometry occur. Our cosmetic transfer is evaluated in the following aspects:

Preservation of hair colors and density. Figure 8 shows an enlarged view of the original eyebrows and eyelashes of the target person so that each hair is clearly seen. The eyebrows and eyelashes of the example and target persons are very different. Note that the hair colors and density of the target face are preserved. Only the cosmetic style has been transferred. Figure 8 also shows the transfer result of a makeup style where the cosmetic covers the eyebrows. Little makeup is applied to eyebrows and eyelashes in these two examples. Mascara, a cosmetic used for coloring and thickening the eyelashes, is not handled in this paper.

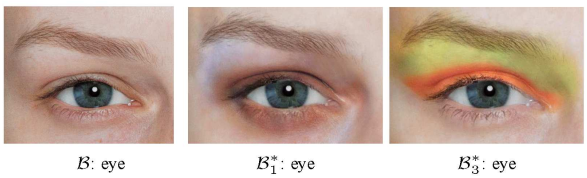

Figure 8: (left) Original eye of *B*. (middle) Preservation of hair colors and density. (right) Cosmetics cover the eyebrows. (A^*_i are examples already shown in Figure 3. B^*_i are our results.)

Style transfer and composition. In addition to the four running examples in previous sections, in Figure 9, we show four additional transfer results. Moreover, we create eight different makeup styles by permuting face/eye styles and lip styles in our cosmetic transfer database. The amount of makeup applied and texture transferred are adjusted using the slide-bars provided in our user interface to improve the visual quality of the results. There are two main user-specified parameters for each of these results, γ to control the amount of coverage and β to control the amount of local texture copy. We list these parameters as (γ, β) for each result in the Table 4. Table cells with two entries are for images that mapped both face/eye styles and lip styles from different sources. For these examples, the top entry is the parameters for the face cosmetic transfer and the bottom is for the lip transfer.

Face 1	Face 2	Face 3	Face 4
Row (c)			
(0.68, 1)	(0.51,1)	(0.39,1)	(0.45,1)
Row (d)			
(0.68, 0.80) (0.28, 1.28)	(0.51, 0.72) (0.63, 1.36)	(0.48, 0.80) (0.08, 1.08)	(0.39, 0.80) (0.10, 0.16)
Row (e)			
(0.45, 0.72) (0.28, 0.92)	(0.63, 0.72) (0.25, 0.56)	(0.68, 0.80) (0.13, 0.44)	(0.38, 0.80) (0.30, 0.92)

Table 1: User-defined parameters for the results shown in Figure 9.

5. Discussion and Limitations

An assumption we have implicitly made is that the cosmetic mapping defined in section 3.2 is multiplicative. In other words, we assume the inherent skin color of *B* before makeup contributes to the skin color after makeup. Fortunately, in most situations, this assumption holds because makeup is normally used to contribute to, instead of cover up, the original skin color. In the extreme cases of heavy makeup, like Beijing Opera actor, our cosmetic transfer model needs the following minor modification:

$$b^*_p = \left((1 - \zeta)\, a^*_p / a_p + \zeta \right) b_p \qquad (3)$$

at each pixel p, where $b_p \in B$, $a_p \in A$, $a^*_p \in A^*$, and $\zeta \in [0, 1]$ is a parameter that controls the *covering strength* of the cosmetics: if the applied cosmetic works like oil paint, ζ should be 1, and values less than 1 reduce the covering power. This covering strength may not be homogeneous throughout the face. For instance, the lip region normally has higher covering strength than other regions on the face.

We use Bayesian matting to segment out eyebrows and eyelashes, and inpainting to repair the resulting holes before cosmetic transfer computation. Finally, we overlay them onto the synthesized image using the alpha matte. We note that the makeup process may sometimes change the geometry of important facial components such as eyelashes. The geometric change of eyelashes due to makeup should consider the difference in hair density between the example person and target person, which is not handled in this paper.

Our approach is quite successful in achieving its goals of cosmetic transfer, however, we do acknowledge that the results are not perfect. In particular, specular highlights on the example pair faces are a problem and are not modeled in our system due to our Lambertian assumption. This can result in some of the images appearing slightly blotches and brighter after the cosmetic transfer. In addition, the proposed method relies heavily on the input alignment of example pairs and target faces to a canonical face. It is not possible to ensure exact accuracy, even manually. This is particularly true for ensuring that the eye lids or the lips of different persons are in exactly the same positions.

While their is room for improvement, our example-based cosmetic transfer is intended as a visualization tool to allow a user to quickly visualize existing styles digitally applied to a new person's face. To this end, our results are quite convincing. As discussed in section 1, cosmetic makeup is an art form and as such the artist cannot and should not be removed from the loop. In a professional context, we envision that example-based cosmetic transfer could be used almost in a browsing manner, where a client could browse through hundreds of existing styles with feedback from a makeup professional who could discuss the appropriateness of existing styles as related to the clients own facial structure and personal preferences.

7. Conclusion

We have presented a technique to effectively transfer the cosmetic contribution encoded in before-and-after images to an image of a new face. Our cosmetic transfer is performed in such a way that skin tone, skin texture, facial hair color and hair density, are faithfully preserved in the input image. Our overall approach provides an effective method to evaluate different cosmetic styles without the need to apply physical makeup. In addition, our technique allows the user to control the magnitude of the makeup transfer and even the ability to blend among different cosmetic styles. Our results demonstrate how computer-graphics can be used in this multibillion dollar industry to provide a rapid and more realistic way to evaluate a large number of example-based cosmetic styles on a person's face.

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Figure 9: Example-based cosmetic transfer. The target face used is B in Figure 1. (a) Example faces before makeup, A_i. (b) Example faces after makeup, A. (c) faces after applying our cosmetic transfer, B^*_i. (d) and (e) Target makeup faces with new styles $B*_{i,j}$, created by combining example face/eye style i, and from example lip style j. Makeup and texture transfer amounts have been adjusted via the user interface of our system, in order to make the composite style suitable to the target person.