Beauty eMakeup: a Deep Makeup Transfer System

Xinyu Ou[1,2,3], Si Liu[1]*, Xiaochun Cao[1], Hefei Ling[2]
[1]SKLOIS, Institute of Information Engineering, Chinese Academy of Sciences
[2]School of Computer Science and Technology, Huazhong University of Science and Technology
[3]YNGBZX, Yunnan Open University
ouxinyu@hust.edu.cn, {liusi,caoxiaochun}@iie.ac.cn, lhefei@hust.edu.cn

ABSTRACT

In this demo, we present a Beauty eMakeup System to automatically recommend the most suitable makeup for a female and synthesis the makeup on her face. Given a before-makeup face, her most suitable makeup is determined automatically. Then, both the before-makeup and the reference faces are fed into the proposed Deep Transfer Network to generate the after-makeup face. Our end-to-end makeup transfer network have several nice properties including: **(1)** with complete functions: including foundation, lip gloss, and eye shadow transfer; **(2)** cosmetic specific: different cosmetics are transferred in different manners; **(3)** localized: different cosmetics are applied on different facial regions; **(4)** producing naturally looking results without obvious artifacts; **(5)** controllable makeup lightness: various results from light makeup to heavy makeup can be generated. Extensive experimental evaluations and analysis on testing images well demonstrate the effectiveness of the proposed system.

Keywords

Beauty eMakeup System; Face Parsing; Makeup Recommendation; Makeup Transfer

1. INTRODUCTION

Makeup is a key factor that influence people's judgment about one's look, especially for female. By choosing proper makeup, one may look more attractive. This demo presents a novel Beauty eMakeup system, which helps users to automatically recommend the most suitable makeup for a female and synthesis the makeup on her face.

As shown in Fig.1, we simulate an applicable makeup process with two functions. **I:** The first function is *makeup recommendation*, where personalization is taken special cares. More specifically, females with similar face, eye or mouth shapes are suitable for similar makeups. The similarity is measured by the Euclidean distance between deep features produced by an off-the-shelf deep face recognition network.

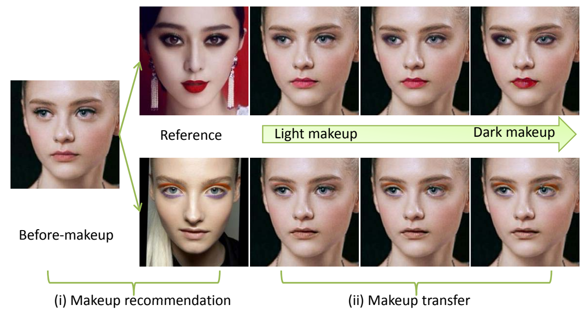


Figure 1: System flowchart.

To sum up, the recommendation is personalized, data-driven and easy to implement. **II:** The second function is *makeup transfer* from the reference face to the before-makeup face. We propose a Deep Localized Makeup Transfer Network(DLMTnet) to achieve face parsing, makeup learning and makeup transfer. Firstly, both before-makeup and reference faces are fed into a face parsing network to generate two corresponding labelmaps. The DLMTnet is based on the Fully Convolutional Networks by (i) emphasizing the makeup relevant facial parts, such as eye shadow and (ii) considering the symmetry structure of the frontal faces. Based on the parsing results, the local region of the before-makeup face (e.g., mouth) corresponds to its counterpart (e.g., lip) in the reference face. Secondly, three most common cosmetics, i.e, eye shadow, lip gloss and foundation are transferred in their own manners. The after-makeup face is initialized as the before-makeup face, then gradually updated via Stochastic Gradient Descent to produce naturally looking results. By tuning up the weight of each cosmetic, a series of after-makeup faces with increasingly heavier makeup can be generated. In this way, our system can produce various results with controllable makeup lightness.

2. TECHNOLOGY

In this Section, we sequentially introduce our makeup recommendation and makeup transfer methods in detail.

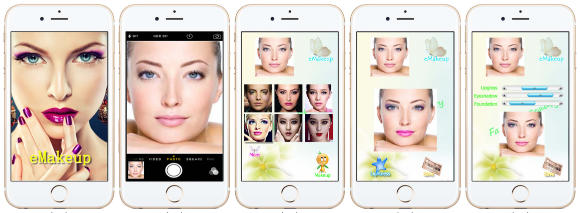
Makeup Recommendation Given a before-makeup face, we find several similar faces from the reference dataset. The similarities are defined as the Euclidean distances between the deep features extracted by feeding the face into an off-the-shelf face recognition model named VGG-Face. The experiment shows that the recommended reference faces have similar facial shapes with the before-makeup faces, and therefore the recommendation is personalized.

Facial Parts vs. Cosmetics Correspondence In or-

*Si Liu is the corresponding author.

MM '16 October 15-19, 2016, Amsterdam, Netherlands

ACM ISBN 978-1-4503-3603-1/16/10…$15.00
DOI: http://dx.doi.org/10.1145/2964284.2973812



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

Figure 2: The user interface of Beauty eMakeup system on a mobile devices. (a) welcome,(b) photo taking, (c) makeup recommendation and choice, (d) synthesis, (e) Lightness Control.

der to transfer the makeup, we need build the correspondence between facial parts of the before-makeup face and the cosmetic regions of the reference face. As a result, the cosmetic can be between the matched pairs. Most of the correspondences can be obtained by the face parsing results. But, the eye shadow of the reference need to warp to match the before-makeup face.

(1) **Face parsing** model is based on the Fully Convolution Network, but we pay more attention to the makeup relevant labels. we propose a *weighted cross-entropy loss* which is a weighted sum over the spatial dimensions of the final layer:

$$\ell\left(x;\theta\right)=\sum\nolimits_{ij}\ell'\left(\mathrm{y}_{ij},p\left(x_{ij};\theta\right)\right)\cdot w\left(y_{ij}\right), \tag{1}$$

where ℓ' is the cross entropy loss defined on each pixel. y_{ij} and $p\left(x_{ij};\theta\right)$ are the ground truth and predicted label of the pixel x_{ij}, and $w\left(y_{ij}\right)$ is the label weight. The weight is set empirically by maximizing the F1 score in the validation set.

(2) **Eye shadow warping** are used to handle the problem of the shapes of eyes and eye brows are different in before-makeup photo and reference photo.

Makeup Transfer Makeup transfer is conducted based on the correspondences among image pairs. In this work, the **Overall Makeup Transfer** considers eye shadow, lip gloss and foundation, and also preserves the face structure.

$$\begin{aligned} A^{*}= & \underset{A\in R^{H\times W\times C}}{\arg\min}\ \lambda_{e}\left(R_{l}(A)+R_{r}(A)\right)+\lambda_{f}R_{f}(A) \\ & +\lambda_{l}\left(R_{up}(A)+R_{low}(A)\right)+\lambda_{s}R_{s}(A)+R_{V^{\beta}}(A) \end{aligned} \tag{2}$$

To make the results more natural, the total variance term $R_{V^{\beta}}=\sum_{i,j}\left((A_{i,j+1}-A_{ij})^{2}+(A_{i+1,j}-A_{ij})^{2}\right)^{\frac{\beta}{2}}$ is added. $R_l(A)$, $R_r(A)$, $R_f(A)$, $R_{up}(A)$, $R_{low}(A)$ and $R_s(A)$ are the left, right eye shadow, foundation, upper, lower lip gloss and face structure loss. And λ_e, λ_f, λ_l and λ_e are the weights to balance different cosmetics. By tuning these weights, the lightness of makeup can be adjusted. For example, by increasing the λ_e, the eye shadow will be darker. The overall energy function (2) is optimized via Stochastic Gradient Descent (SGD) by using momentum.

3. USER INTERFACE

The Beauty eMakeup system is a mobile APP, it has multiple screens. After entering the welcome screen in Fig.2(a), the user can choose to take or upload a non-makeup photo, shown in Fig.2(b). After that, system will automatically enter the makeup recommendation screen, and a set of the most suitable makeup girls are displayed to user, as shown in Fig.2(c). In this screen, user can choose a favourite model and press the "Makeup" button to synthesize the makeup photo or press the "More" button to automatic replace another group of the makeup girls. Fig.2(d) shows the makeup photo, which is synthesized by non-makeup photo and reference photo. A "Save" button allows user to save the makeup photo, while the "Lightness" button permit user to adjust the lightness of each makeup part, such as lip gloss, eye shadow, and foundation in Fig.2(e). Another "save" button is designed on this screen to allow user to save her/his photo.

Besides, we will develop a eMakeup system for PC user.

4. DEMONSTRATION

We compare with DFace [3], NerualStyle [1], the results is conducted both qualitatively and quantitatively. Furthermore, in order to show our method can generate after-makeup face with various makeup lightness, ranging from light makeup to dark makeup, we gradually increase certain makeup weights λ_e, λ_f and λ_l, one result is shown in Fig.1 For each before-makeup face, we select serval most similar looking reference girls, and transfer their makeup to the before-makeup face, Fig.3 shown the effect picture. This function is quite useful in real application, because the users can virtually try different makeup and choose the favorite one. More experiment details, please refer to [4].

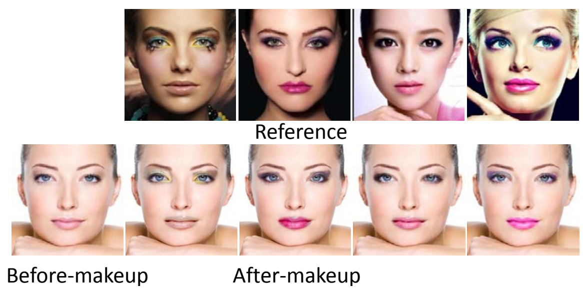


Figure 3: The same girl wears different makeups.

5. CONCLUSIONS

In this demo, we showcase a novel Deep Localized Makeup Transfer Network to automatically transfer the makeup from a reference face to a before-makeup face. In the future, we plan to explore the extensibility of the network. For example, one before-makeup face can be combined with two reference faces. The after-makeup face has the eye shadow of one reference face and lip gloss of another reference face. Moreover, we also want to integrate the makeup system into human parsing [2].

6. ACKNOWLEDGMENTS

This work was supported in part by the Natural Science Foundation of China under Grant U1536203 and 61272409, in part by the Major Scientific and Technological Innovation Project of Hubei Province under Grant 2015AAA013.

7. REFERENCES

[1] L. A. Gatys, A. S. Ecker, and M. Bethge., A neural algorithm of artistic style. *CoRR*, abs/1508.06576, 2015.

[2] S. Liu, X. Liang, L. Liu, X. Shen, J. Yang, C. Xu, L. Lin, X. Cao, and S. Yan. Matching-cnn meets knn: Quasi-parametric human parsing. *In Computer Vision and Pattern Recognition*, pages 1419-1427, 2015.

[3] D. Guo and T. Sim. Digital face makeup by example. *In Computer Vision and Pattern Recognition*, pages 73-79, 2009.

[4] S. Liu, X. Ou, R. Qian, W. Wang, and X. Cao. Makeup like a superstar: Deep localized makeup transfer network. 2016.