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FaceMore: A Face Beautification Platform on the Cloud

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***Abstract*—FaceMore, a cloud-based face beautification platform for intelligent face manipulation, is developed in this work. It provides flexible and efficient cloud API to develop automatic or interactive face retouching applications. A web-site, www.facemore.net, is built on FaceMore, where user can upload images and obtain various online face beautification services. To obtain automatic inhomogeneous editing effects in a natural and efficient manner, we analyze the novel tool, called region-aware mask, from semi-supervised learning perspective. We reformulate the optimized-based model of region-aware mask using label propagation, and propose a fast approximate algorithm for mask generation, which leads to about 40% speed improvement while maintain high visual quality for face beatification. Qualitative and quantitative evaluations were performed for mask generation and face beatification. Comparisons with five representative commercial systems, including PicTreat, Portraiture, Portrait+, Meitu and Baidu Motu, illustrate the effectiveness of our system for image enhancement of facial lighting, smoothness and color.**

***Index Terms*—Face beautification, region-aware mask, label propagation, edit propagation, cloud computing.**

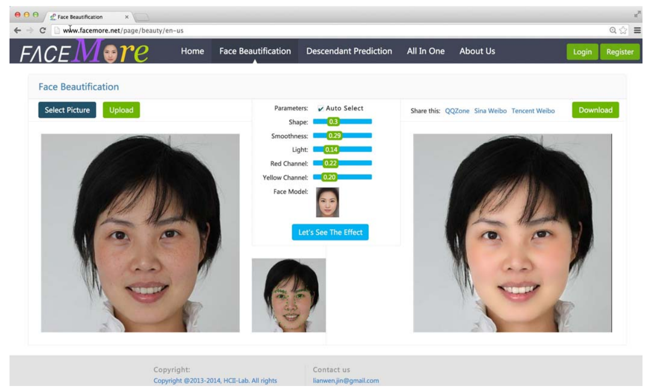

Fig. 1: A web-site (www.facemore.net) built on the FaceMore platform.

I. Introduction

Recently, machine analysis of facial beauty has lead to many research in the realm of computer vision [1], [2], [3], [4], machine learning [5], [6], [7] and computer graphics [9], [14], [10]. *Face beautification* is one of the important problems in facial beauty analysis, which aims to create enhanced aesthetic appeal of human face images, while maintain high similarity with the original image [9].

Psychology research indicates that facial lighting, smoothness and color are three important factors affecting human perception of facial attractiveness [16], [17]. Face beautification can be achieved through the manipulation of the facial appearance features. Although Some commercial image editing software systems are available (such as Adobe Photoshop) for these tasks, face image retouching is still time-consuming due to the tedious operations. It would be fascinating to perform automatic facial beautification, but there are two challenges to overcome. First, it is difficult for a human to achieve local inhomogeneous facial editing with good visual consistence, no matter for automatic manipulation of a machine. Second, some facial editing operation requires solving a very large linear system, which comes at high computational cost.

Methods and techniques were developed for automatic face beatification. Lee et al. [13] achieved facial smoothness enhancement using a skin segmentation map, which is generated by the combination of Gaussian mixture model and Bayesian segmentation. Chen et al. [12] performed facial color enhancement based on color temperature-insensitive skin color detection, bilateral filter and Poisson image cloning. Florea et al. [11] used skin detection and a Lee filter for HD video camera face enhancement. Liu et al. [2] proposed an automatic system, Beauty e-Experts, for hairstyle and facial makeup recommendation and synthesis. Some commercial face retouching systems are also available, such as PicTreat [18], Portrait+ [20], Portraiture [19], MeiTu [21], Baidu Motu [22] etc. However, the problem of automatic local inhomogeneous facial editing is still not well solved by the previous methods and systems, which may introduce some visual artifact in the image, such as the global tonal changes or facial blur.

Recently, Liang et al. [1], [8] proposed a novel tool, called *region-aware mask*, for adaptive facial manipulation. The mask is initialized by automatic face landmark detection [25], and propagated according to the face feature and gradient so that to fit the region boundary closely and produce adaptive transition between different regions [8]. Experiments show that the state-of-the-art face beautification results are obtained using region-aware mask [1]. However, the implementation of region-aware mask require to solve a $n*n$ dimension matrix equation, where n is the pixel number of the image. When the spatial resolution of a image is large, the computing cost is considerable.

In this paper, we implement automatic manipulation of

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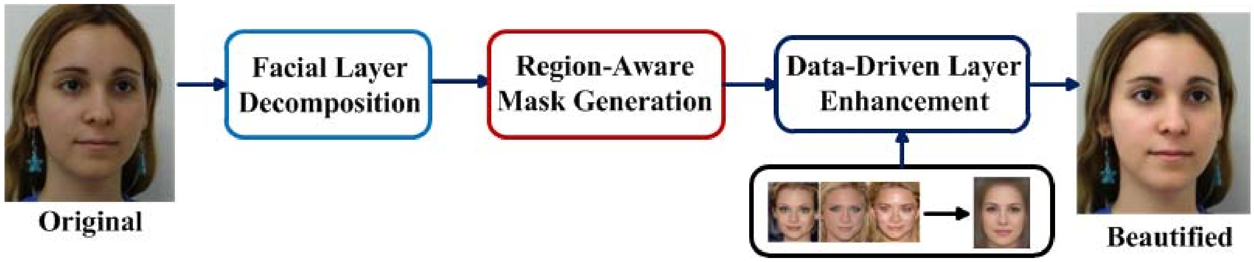


Fig. 2: The framework of face beautification contains three stages. **Facial layer decomposition** separates the original image into lighting, detail and color layers. **Region-aware mask generation** produces mask for adaptive region selection and local manipulation. **Data-driven layer enhancement** provides automatic parameters setting scheme according to some psychological assumption.

facial lighting, smoothness and color based on region-aware mask [1], and propose a fast approximation algorithm for mask generation. We reformulate region-aware mask from semi-supervised learning perspective [27], and derive the mathematical relationship between the energy minimization model of mask generation and the iterated label propagation [28]. Furthermore, we find that under certain assumption, the limit case of the label propagation lead to an approximate algorithm for region-aware mask, which converts the original large linear system to a much smaller one. Experiments illustrate that the approximation method for region-aware mask efficiently improve the computation speed while maintain high visual quality for face beatification.

Then, a cloud-based face beautification platform, called FaceMore, is built on Windows Azure. FaceMore offers a flexible and efficient scheme for different face manipulation service. The algorithms of region-aware mask, average face generation, and face beautification are integrated in FaceMore cloud API, which can be used to develop automatic or interactive face manipulation applications. Since the major computation and data storage are implemented on the cloud server, the application can run efficiently in a computation-limited device, like smartphone. An online face manipulation website, **www.facemore.net**, is constructed based on FaceMore, where user can upload images and obtain various online face beautification service, as shown in Fig. 1.

In summary, the specific contributions of this paper include:

- An approximation algorithm for region-aware mask [1], which is based on the limit property of label propagation.
- A cloud-based face beautification platform called FaceMore, which is provide intelligent facial manipulation service for different applications.
- A web-site (www.facemore.net) built on FaceMore platform, which offers online automatic and interactive face beautification application.

II. Face Beautification Framework

Face beautification involves image editing for different face appearance feature, like facial lighting, details and color. It consists three main stages, facial layer decomposition, region-aware mask generation and data-driven layer enhancement, as shown in Fig. 2.

A. Facial Layer Decomposition

The input image is separated as facial lighting, detail and color layers, and the following operations are performed in the corresponding layer.

First, the original image I is converted into CIELAB color space, which contains one luminance channel L^* (I^{L^*}) and two chromaticity channels a^*, b^*. The chromaticity channels are regarded as the color layer I^c. Second, an edge-preserving smoothing operator, like WLS filter [26], is used to capture the large-scale lighting variations in I^{L^*}, and obtain the lighting layer I^L. Third, the detail layer I^d is obtained by subtracting I^L from I^{L^*}, i.e. $I^d = I^{L^*} - I^L$.

B. Region-Aware Mask Generation

Facial mask is essential to implement local inhomogeneous facial manipulation, which is used to select the editing region and set the relative editing level for different regions. The region-aware mask proposed in [1] can fit the complex region boundary adaptively according the similarity of different regions, which is superior to the mask that is generated by face segmentation. Therefore, we use region-aware mask for face manipulation in the framework.

However, the original mask generation method involve a quadratic functional optimization problem and requires solving a large linear system, which comes at a considerable computation cost for high spatial resolution image. We find that the mask generation has a closely relationship with semi-supervised learning [27], and the mask diffusion can be reformulated as an iterated label propagation [28]. Furthermore, an efficient approximate algorithm is proposed based on the analysis of the limit case of label propagation, which reduces the computation complexity efficiently. The mathematical derivation and analysis are discussed in details in Section III.

C. Data-Driven Layer Enhancement

We denote the lighting, detail and color layers of the original image as I^L, I^d and I^c; the corresponding facial masks as M^L, M^d and M^c; the beautified outputs as O^L, O^d and O^c, respectively. Layer enhancement is implemented as follows:

$$\begin{cases} O^L = I^L(1 + M^L * w^L) \\ O^d = I^d(1 - M^d * w^d) \\ O^c = I^c(1 + M^c * w^c) \end{cases} \tag{1}$$

where scalar values w^L, w^d and w^c are used to control the global adjustment degree, and local inhomogeneous editing is implemented through the masks.

The scalar values $w^{\{L,d,c\}}$ can be adjusted by user interaction, but it can also be set according to facial attractiveness prediction for automatic facial manipulation. To simplify the analysis, we follow the data-driven scheme of average face and psychological priors proposed in [1] for the automatic initialization of the scalar values.

III. Fast Algorithm for Region-Aware Mask

In [1], region-aware mask is based on an edge-preserving energy minimization model [15]. To ensure the clarity of presentation, we denote the mask constraint initialized by facial landmarks as M', the region-aware mask output as M, and the feature which guide the diffusion of mask information as G. The region-aware mask is obtained by minimizing the following quadratic cost function:

$$C(M) = \sum_i S_i(M_i - M_i')^2 + \lambda \sum_{i,j} W_{ij}(M_i - M_j)^2 \tag{2}$$

In Eq. (2), S is a diagonal $n \times n$ matrix given by $S_i = 1$ in the constraint region, otherwise $S_i = 0$; λ is used to balance the relative weights of the two terms. The weight matrix $W_{ij} = \frac{1}{\|G_i - G_j\|^\alpha + \varepsilon}$. It is controlled by two parameters, where ε is a small constant that prevents division by zero; α controls the diffusion sensitivity to the gradients of G.

To concentrate our research on the computation issue of mask generation, the parameters are set to the typical values $\varepsilon = 0.0001$, $\alpha = 1$ in this paper.

A. Relationship with Label Propagation

Region-aware is regarded as an edit propagation [15], [29] with automatic mask initialization in [1]. We find that the mask diffusion process can be also interpreted in a semi-supervised learning perspective [27], and region-aware can be implemented by an iterated label propagation method [28].

The smoothness property of the mask is mainly determined by the second term in Eq. (2), and it has a closely relationship with graph Laplacian.

$$\begin{aligned} \sum_{i,j} W_{ij}(M_i - M_j)^2 &= 2\sum_{i=1}^{n} M_i^2 \sum_{j=1}^{n} W_{ij} - 2\sum_{i.j=1}^{n} W_{ij} M_i M_j \\ &= 2M^\top (D - W) M \\ &= 2M^\top L M \end{aligned}$$

where, D is a diagonal matrix with $D_{ii} = \sum_j W_{ij}$, and $L = D - W$ is the un-normalized graph Laplacian. Then, a more compact form of cost function is obtained.

$$C(M) = \|S(M - M')\|^2 + 2\lambda M^\top L M \tag{3}$$

The derivative of the cost is

$$\begin{aligned} \frac{1}{2}\frac{\partial C(M)}{\partial M} &= S(M - M') + \lambda L M \\ &= (S + \lambda L)M - SM' \\ \Rightarrow M &= (S + \lambda L)^{-1} S M' \end{aligned} \tag{4}$$

When the derivative is set to 0, the cost can be minimized using a Jacobi iteration, which is the label propagation proposed by Zhu and Ghahramani [28], except for the similarity metric in the weight matrix W_{ij}:

$$M^{(t+1)} = (S + \lambda D)^{-1}(\lambda W M^{(t)} + S M'). \tag{5}$$

Therefore, region-aware mask generation is in fact a label propagation with a similarity metric determined by the guided feature.

B. Approximation Solution

We find that under the assumption that the initialized mask region is mostly correct, region-aware mask can be approximated using the limit property of the label propagation.

We denote $M = (M_l, M_u)$, where M_l is the labeled mask region initialized by M', and M_u is the unlabeled mask region determined by label propagation. If we asssume that the initialized mask region is mostly correct, the cost Eq.(3) is dominated by $\|S(M - M')\|^2$, which means $\lambda \to 0$ and $SM = SM' \Rightarrow M_l = M_l'$. Then the minimization of cost Eq.(3) leads to

$$\underset{M}{min.} C(M) \Rightarrow \begin{cases} \underset{M}{min.}(M^\top L M) \\ s.t.\ M_l = M_l'. \end{cases} \tag{6}$$

Minimize $M^T L M$ with respect to M_u:

$$\underset{M_u}{min.} \left[M_l^\top, M_u^\top\right] \begin{pmatrix} L_{ll} & L_{lu} \\ L_{ul} & L_{uu} \end{pmatrix} \begin{bmatrix} M_l \\ M_u \end{bmatrix} \tag{7}$$

$$\begin{aligned} &\Rightarrow \underset{M_u}{min.}(2M_u^\top L_{ul} M_l + M_u^\top L_{uu} M_u) \\ &\Rightarrow L_{ul} M_l' + L_{uu} M_u = 0 \\ &\Rightarrow L_{uu} M_u = -L_{ul} M_l' \end{aligned}$$

we obtain that

$$\begin{cases} M_l = M_l' \\ M_u = -L_{uu}^{-1} L_{ul} M_l'. \end{cases} \tag{8}$$

C. Analysis

We denote the pixel number of the image as n, and the unlabeled pixel number as u. Comparing Eq. (4) and Eq. (8), M is obtained through solving a linear system with complexity of n^2 and u^2 respectively. The unlabeled mask region is a small part of the image, and we can make it much smaller if it is restricted into a bounding box of face detection. Therefore, u can be much smaller than n, and the approximation method intrinsically reduces the computational complexity of the region-aware mask. Experiments about numerical accuracy and computational speed illustrate the efficiency of the approximation method, and more details are discussed in Section V.

IV. Cloud-Based Face Beautification Architecture

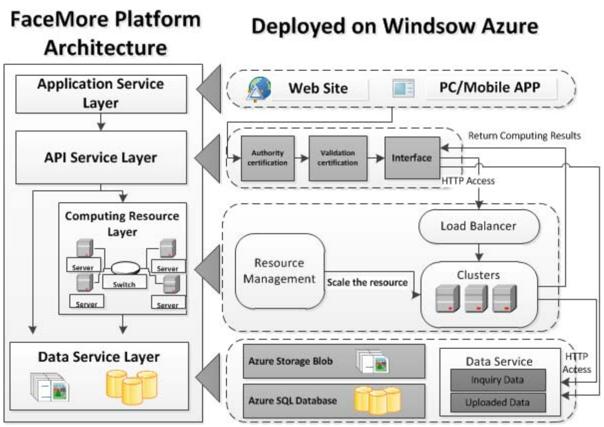


Fig. 3: The cloud architecture of FaceMore on Windows Azure.

A cloud-based platform, called FaceMore, is built on Windows Azure, which contains four layers, as shown in Fig. 3.

Application Services Layer. On the top is the application services Layer, which provide application service for user using the face beautification algorithm and the related computation and data storage resource. To evaluate the FaceMore platform, a web-site (www.facemore.net) is built, which offers user interface for different online face manipulation services, as shown in Fig. 1.

API Service Layer. It provides interface of face beautification algorithm and perform permission analysis of the API call request. API service acquires computational resource through HTTP access from the computing resource layer and data service layer.

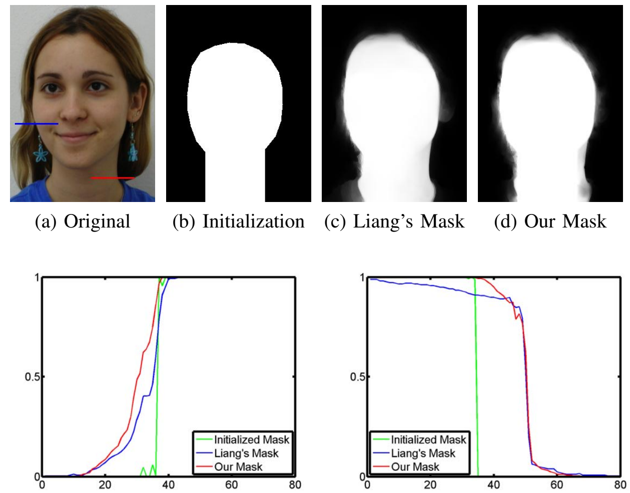
Computing Resource layer. The face beautification algorithms are implemented in this layer. Since the real-time face manipulation service requires large computational resource, this layer provides load balance of the clusters and resource management to scale the computational resource automatically.

Data Service Layer. The data of algorithm, like images and facial mask, and the data of the application, like website monitoring log, are stored in this layer. The layer use Azure Storage services, which distributes file in the cloud, and provides synchronized data service.

V. Experiments

A. Evaluations for Mask Generation

We made both qualitative and quantitative experiments to evaluate the mask approximation method of label propagation. The qualitative comparisons of the region-aware mask of [1] and our methods are in Fig. 4 The results of Fig. 4(c) and Fig. 4(d) indicate that the masks share high global similarity. Both the masks are propagated efficiently and fit the facial boundary closely. Fig. 4(e) and Fig. 4(f) plot the pixel value alone the blue and red horizontal line in the face respectively, and it can be observed that the value of the masks in the local region are highly consistent.



(a) Original (b) Initialization (c) Liang's Mask (d) Our Mask

(e) Comparison along the blue line (f) Comparison along the red line

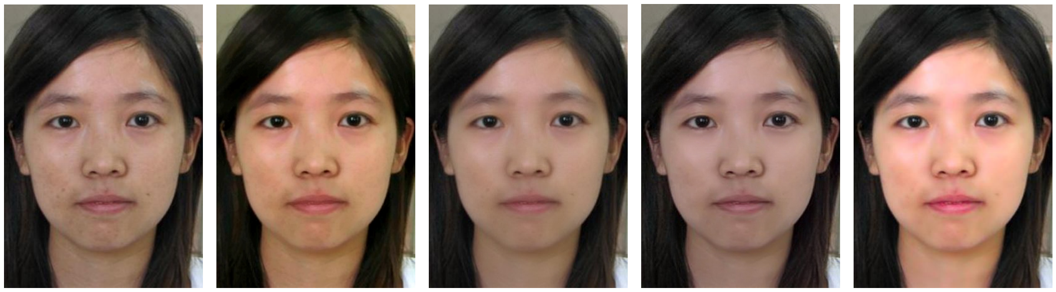
Fig. 4: Analysis of numerical accuracy of the mask generation. The results show that the approximated mask (d) of our method has high similarity to Liang's [1] region-aware mask (c).

A qualitative experiments are made on the Part Labels Database [31] for face segmentation, which contains 2927 coarsely aligned faces with superpixel-wise hair/skin/background labels. The original PLD is divided into training, validation and testing sets that contain 1500, 500 and 927 samples, respectively. We use the facial mask to perform skin/background segmentation to evaluate the numerical accuracy of mask generation. Therefore, the hair labels are converted to background labels and we selected 600 faces without much hair and pose occlusions from 927 testing set for evaluation.

We used the active shape model (ASM) [25], lighting mask (LMask) of [1], lighting mask generated by label propagation (LPMask) in this paper to perform skin/background superpixel-wise segmentation. The accuracy of ASM, LMask and LPMask are 92.49%, 95.32% and 94.79% respectively. The results indicate that the label propagation method has a high numerical accuracy to approximate region-aware mask. For a 364*268 image, the running time of Jacobi iteration for LMask is 1.39s, while LPMask is 0.82s with about 40% speed improvement. Note that more sophisticated numerical method, like multi-level preconditioning [32], can further increase the computational speed, which merits future exploration.

B. Evaluations for Face Beautification

We performed face beautification on the Caltech [23], FEI [24], and Lifespan [30] face database, as shown in Fig. 5. The results demonstrate the effectiveness of our method for facial enhancement, and we observe that unwanted wrinkles and spots in the skin region are removed, while significant details and attributes were retained in the non-skin regions.



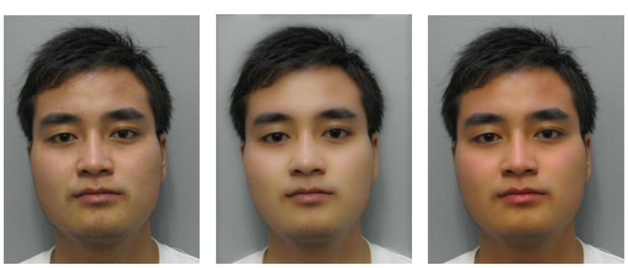
(a) Original (b) PicTreat (c) Portraiture (d) Portrait+ (e) Ours

Fig. 6: Comparison with the commercial systems PicTreat [18], Portraiture [19] and Portrait+ [20] for face beautification.

(a) Original (b) Meitu's Smoothing (c) Ours Smoothing (d) Meitu's Auto (e) Ours Auto

Fig. 7: Comparison with commercial system Meitu [21] for face beautification under different automatic scheme.

Fig. 5: Automatic beautification for faces with different genders, expression and ages. The input faces (top) on were taken in the Caltech, FEI, and Lifespan face database.



(a) Original (b) Baidu Motu (c) Ours

Fig. 8: Comparison with commercial system Baidu Motu [22].

C. Comparisons with Commercial Systems

We compared our face manipulation system with five representative commercial systems, including PicTreat [18], Portraiture [19] and Portrait+ [20], Meitu [21] and Baidu Motu [22]. Since the technical details of the systems are not open, we chose the most similar scheme of each system for comparison.

Fig. 6 shows the results of the first three systems and ours. It can be observed that PicTreat in inclined to globally adjust the lighting and the color of the image, but little smoothness enhancement. Portraiture and Portrait+ provide effective smoothness manipulation schemes to remove unwanted facial wrinkles and spots, while preserved the lighting of the original image. Our system covers facial smoothness, lighting, and color enhancement completely and produced a face with highly visual consistency.

In Fig. 7, we compare the Meitu and our system for automatic smoothing and face enhancement. The results indicate that Meitu is inclined to remove the details of the whole image, which lead to reduce the contrast of the image, while our methods perform region-aware smoothing, which preserve the significant facial details well. Although Meitu offer many tools for face manipulation, most of them requires manual selection and repeated operations. In contrast, the region-aware mask allows our system to perform automatic editing in local facial region in adaptive manners.

We also compared our system with Baidu Motu, as shown in Fig. 8. Although both the systems beautify the faces effectively, the smoothness enhancement of Baidu Motu introduce some visual blur to the image, while ours reserve the significant feature of the image well.

VI. Conclusions

In this work, we developed a flexible and efficient cloud-based face beatification platform, called FaceMore, for intelligent face manipulation. Using the cloud API of FaceMore, a web-site (www.facemore.net) is built to offer various online face beautification services. Since FaceMore is based on the state-of-the-art region-aware mask techniques, face editing with high visual consistence can be obtained automatically without the tedious and time-consuming operations.

The computation problem of region-aware mask was also considered. We derive the mathematical relationship between the energy minimization model of region-aware mask [1] and label propagation [28], which means mask diffusion can be interpreted from semi-supervised learning perspective and much more face manipulation tools can be developed using sophisticated semi-supervised learning models [27].

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