Virtual Makeup Based on Golden Sample Search

Ping Wang[1], Mao-Hsiung Hung[2], Chaur-Heh Hsieh[1], Jen-Yang Chen[3*]

[1] College of Artificial Intelligence, Yango University, China
[2] School of Computer Science and Mathematics, Fujian University of Technology, China
[3] Department of Electronic Engineering, Ming Chuan University, Taiwan
pwang@ygu.edu.cn, mhhung0502@qq.com, chaoho1204@qq.com, jychen@mail.mcu.edu.tw

Abstract

Virtual makeup is expected to provide customers with an approximate experience of actual trial. This paper proposes a novel virtual makeup system based on golden-sample search scheme. A golden-sample database is built offline, which contains canonical patterns of facial components to be made-up. A novel feature representation of the pattern is developed, which makes the golden-sample search effective and efficient. In online phase, users select the markup region and colors they like. The representative feature vector of the selected markup region is used to search the database to find the best-matching pattern. Then, the best-matching pattern is colored and stitched to the input image. The system can process the dynamic image from camera, and thus the user can observe whether the makeup effect under different facial poses is appropriate, and then make corresponding makeup adjustments. The experimental results indicate our system provides nature and good visual effects in makeup.

Keywords: Virtual makeup, Golden sample search, Image stitching

1 Introduction

People have used facial makeup to improve or alter their appearance for thousands of years. Cosmetic trial is one of most important steps in makeup sale. The trials provide customers reference to pick and buy cosmetic products. Except actual makeup trials, digital makeup or virtual makeup is expected to be an alternative to provide approximate experiences to customers. Especially, internet usage is booming today; remote virtual makeup through the Internet will be even more important in the future. Therefore, a virtual makeup system has become one of significant tools in marketing and sale of cosmetic industry.

A typical processing flow of traditional virtual makeup methods [1-2] is shown in Figure 1. First, feature points are detected from an input face image. Then, under the guide of feature points, makeup regions including eyes, eyebrows, nose and lips are segmented from the face image. Next, colors selected by users are applied to the segmented regions. Finally, the colored region images are stitched to the face image. In order to reach the high accuracy of region segmentations, some complicated methods of ethnicity skin detection and active shape model are suggested in [1].

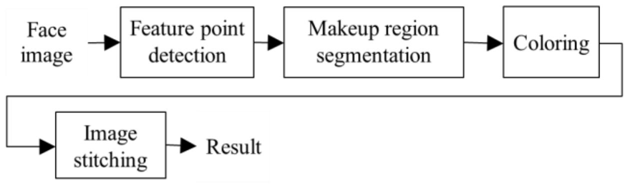


Figure 1. Traditional virtual makeup flow

Several more advanced virtual makeup algorithms [3-5] are proposed based on an example scheme. In the example-based algorithms, a pair of images is utilized to complete the virtual makeup. One is a subject image to be made-up, which is captured from a user's face; the other is an example style face image of a model with putting on makeup. The virtual makeup is regarded as the synthesis process of subject and example images. The example image is first warped to align to the subject image. Then the subject image and warped example image are decomposed into structure, skin detail and color layers. Finally the skin detail and color layers of the warped example image are transferred to the subject image while preserving the face structure layer of the subject image.

The work in [6] proposes a virtual makeup method based on personal color. In the makeup of a particular facial region of a user, optimal makeup color that suits well for the user is extracted from the predefined database by analyzing the face color of the user. The makeup parts such as foundation, blush, lipstick, eyeliner, and eyeshadow in the database become examples and provide the selection to produce a virtual makeup on the user's face image.

In [7], a deep neural network is proposed to build a recommendation model that is trained from examples and knowledge base rules jointly. Each makeup-related facial trait is classified into certain classes and coded as a feature vector. The classified information is helpful to train the recommendation model. Using the model, appropriate colors and styles are recommended to the synthesis process and the makeup result yields. The advantage of the method is that it can achieve homogeneous makeup style which fits face according to the classified facial traits.

Differing from the existing methods above, this work proposes a new virtual makeup method based on golden-sample search, which includes offline and online phases. In offline phase, a database is created, which stores canonical patterns of facial components called golden-sample patterns. In online makeup phase, the representative feature vector of a user-selected makeup region is extracted and used to search

*Corresponding Author: Jen-Yang Chen; E-mail: jychen@mail.mcu.edu.tw
DOI: 10.53106/160792642022112306006

the database to find the best-matching pattern. Then, the best-matching pattern is colored and stitched to the makeup region of the input image. The golden-sample search method avoids the difficulty of the makeup region segmentation and the proposed feature representation makes the search effective and efficient. The experimental results indicate that our proposed system provides quite good vision effects in markup. The major contributions of this article are:

(a) A novel virtual makeup system is developed, which is based on searching the golden-sample patterns of facial components to be made-up.

(b) A new feature representation scheme is proposed, which represents each markup region based on facial landmarks.

The remainder of this paper is organized as follows. Section 2 describes the proposed method, which includes offline database creation and online makeup phases. Section 3 demonstrates the proposed system and discusses the experimental results. The conclusions are drawn in Section 4.

2 Proposed Method

The proposed method contains two phases: (1) offline database creation, and (2) online makeup. The first phase mainly creates canonical patterns of facial components (mouth, eyes, noses, etc.), which represents possible geometrical shapes of the components. During the online phase, a component of the input face is compared to the respective patterns of the database to get the best match. A novel feature representation scheme is proposed, which makes the search effective and efficient. The best-matched pattern is made-up according to the user preference and then is stitched to the respective region. The details are described in the following.

2.1 Offline Database Creation

At this stage, the golden sample database is created offline. A color face image dataset is established first. Then the following steps are performed for each canonical face image in the dataset:

(1) Detect 68 facial landmarks and perform face alignment for normalization

(2) Define makeup regions using the facial landmarks including: (a) left and right eyes, (b) left and right eyebrows, (c) left and right cheeks (d) nose, and (e) lip. Then, create masks (binary image) for each region, which represents the shape of each region.

(3) Calculate feature representation vector of each markup region.

Completing the above steps, we obtain a golden-sample database that includes four types of information for a canonical face: (a) ROI of each markup region, (b) landmark set of each markup region, (c) feature representation of each region and (d) mask of each markup region.

2.1.1 Facial Landmark Extraction

This work employs a machine learning library of Dlib [8] to perform face detection and facial landmark extraction. Dlib extracts HOG (Histogram of Oriented Gradients) features from a training set of face images and then learns SVM detection models based on the features [9]. The trained SVM model detects a bounding box (ROI) containing a face or a component of the face such as mouth for a new input image. After the detection of ROIs, the HOG features are used to match with the predefined patterns to obtain the positions of 68 facial landmarks as shown in Figure 2.

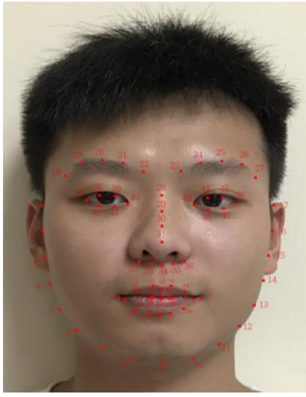


Figure 2. An example of 68 facial landmarks

Since the face images collected are not always frontal, face alignment process should be performed during the phase of golden-sample database collection. We select an image of a standard frontal face to be the reference image and acquire its 68 facial landmarks. Similarly, we extract 68 facial landmarks from each image of the dataset. Then, the one-to-one matching relationships are built between two sets of facial landmarks. Next, we use the matching relationships to estimate a perspective transformation between the reference landmark set and the input landmark set. Finally, each input image is transformed into frontal face geometrically using the estimated transformation matrix to complete face alignment.

2.1.2 Markup Region Definition

After the completion of facial landmarks extraction and face alignment, we segment markup regions and create a golden-sample database accordingly. These markup regions in a face include left and right eyes, left and right eyebrows, left and right cheeks, lip and nose. We pre-define these markup regions according to the positions of the facial landmarks. These markup regions are segmented out of face images captured from volunteers with ages ranging from 20–30 years old. To increase the varieties, we add lip shapes of different expressions such as smile, little-opening, pouting and so on.

The golden-sample database mainly contains three types of data in the following.

(a) Makeup landmark group: a set of the facial landmarks of each region. For example, the set of landmarks 19 to 22 denotes the right eyebrow region.

(b) Makeup ROI (Region of Interest): a rectangle area to be made-up. A total of 8 ROIs is defined in our work, which will be further described in the following subsection.

(c) Makeup region image: a binary image in which the white pixel is the pixel to be made-up. Figure 3 displays an example of a set of makeup regions.

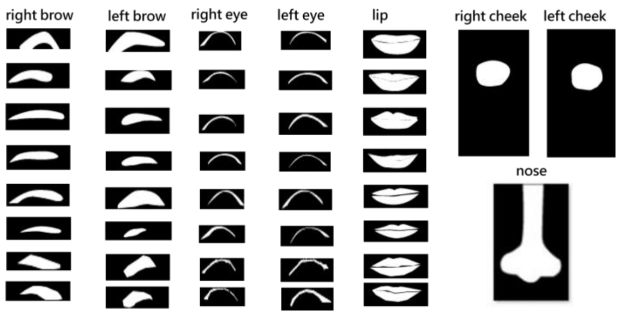


Figure 3. An example of a set of markup regions

2.1.3 Feature Representation

A new feature representation scheme is proposed, which represents each markup region based on facial landmarks. The 68 facial landmarks are clustered into 8 groups according to their geometric relationships. The 8 landmark groups are right/left eyebrows, right/left eyes, right/left cheeks, nose and mouth, as shown in Figure 4. Each landmark group is composed of several landmark points. We calculate the representative features for each group as follows.

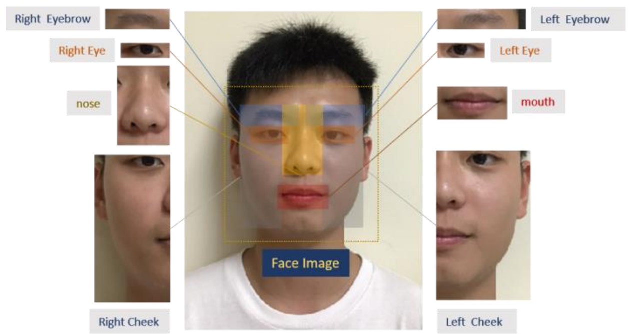


Figure 4. Eight components in a face image

First, we select a pair of points from a landmark group which forms the longest line. The line is referred to as a baseline. Figure 5 shows landmarks and baselines (marked in red) related to markup regions. For example, we select two points of mouth corners to form a baseline. Then, the baseline and any other point can build a triangle.

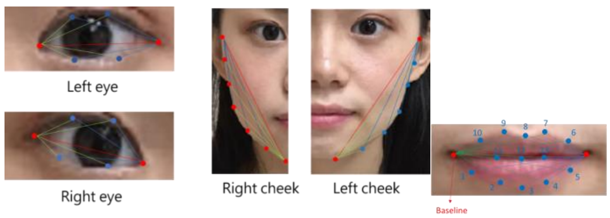


Figure 5. Landmarks and baselines related to markup regions

Assume a point in the mouth group is denoted as xi. The point and the baseline constructs a triangle shown in Figure 6. We denote $\mathbf{x}_i$ as the vector formed by $\mathbf{x}_i$ and one endpoint of the baseline, and $\mathbf{b}$ as the vector of the baseline. Two cosine values of the two angles of α_i and β_i, u_i and v_i, can be calculated by $\mathbf{x}_i$ and $\mathbf{b}$ as

$$u_i = cos(\alpha_i) = \frac{\mathbf{x}_i \cdot \mathbf{b}}{\|\mathbf{x}_i\|\|\mathbf{b}\|}, v_i = \cos(\beta_i) = \frac{(\mathbf{x}_i - \mathbf{b})\cdot(-\mathbf{b})}{\|\mathbf{x}_i - \mathbf{b}\|\|-\mathbf{b}\|}, \quad \textbf{(1)}$$

where || denotes the 2-norm of a vector, and the operator is the inner product of the two vectors. Here, a landmark point xi generates a 2-D vector (u_i,v_i).

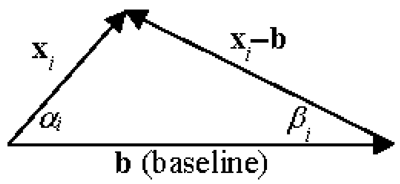


Figure 6. Triangle formed by a baseline and a point x_i

For a landmark group with n points, we can obtain a set of 2-D vectors (u_1,v_1), (u_2,v_2),…, (u_n, v_n). Concatenating these vectors, we can obtain a feature vector with dimension of $2n$ as

$$\mathbf{w} = [u_1, v_1, u_2, v_2, \ldots, u_n, v_n]. \quad \textbf{(2)}$$

It is noted that each markup region is represented by a feature vector. During the offline phase, the feature vectors of all markup regions are formed into golden-sample database.

2.2 Online Makeup

Figure 7 shows the flow of online makeup for a facial component and the procedure is described as follows.

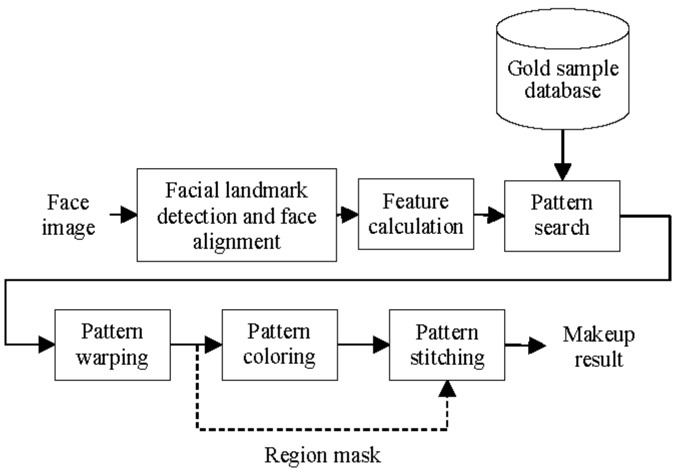


Figure 7. Online makeup flow chart

Step 1. Detect face and facial landmarks for an input face image. Then, perform face alignment; that is, using a reference frontal face image and the input face image to calculate transform matrix, T_1. Next, align the pose of the input face image into frontal by perform transformation using T_1.
Step 2. Select a markup target according to the user's input. Calculate a feature representation vector of the selected markup target using Eq. (1) and (2).
Step 3. Search the best-match pattern from a database of golden samples using the feature representation vector. See the detail in 2.2.1.
Step 4. Calculate a transform matrix of T_2 between the best-match pattern to the selected target. Then, warp the best-match pattern using T_2. It is noted that T_2 is a local transform, while T_1 is a global transform.

Step 5. Color the warped pattern according to the color user selected.
Step 6. Stitch the resulting pattern to the corresponding region of the face.

2.2.1 Patten Search

As described before, each golden sample pattern in the golden-sample database has its own feature vector of $\boldsymbol{w}_i$. In the markup phase, we calculate feature vector $\boldsymbol{x}$ for the user selected markup region. Thus in this step, by calculating the Euclidean distances between $\boldsymbol{x}$ and $\boldsymbol{w}_i$ for all i, and selecting the pattern which has the minimal distance, we can get the best-match pattern, which can be represented as

$$i^* = argmin_{i=1,2,..,N} \|\mathbf{x} - \mathbf{w}_i\|_2, \tag{3}$$

where $\|\mathbf{x}-\mathbf{w}_i\|_2$ is the Euclidean distance of two vectors.

2.2.2 Patten Warping

The pattern search above obtains the pattern which is most similar to the shape of the markup region of a particular user. However, there exists possible pose variations including position, rotation and scaling between the pattern and the markup region of the current user. Therefore, we further compensate the pose variation with pattern warping to achieve accurate fit in pattern stitching. In warping, it needs to estimate geometrical transformation matrix between the best-match pattern (BMP) and selected markup target (SMT). For each markup region, we select four pairs of corresponding keypoints from facial landmarks in BMP and SMT to calculate the warping transformation. The four keypoints in BMP and SMT are denoted respectively by $e_1(x_1,y_1)$, $e_2(x_2,y_2)$, $e_3(x_3,y_3)$, $e_4(x_4,y_4)$ and $e_1(x'_1,y'_1)$, $e_2(x'_2,y'_2)$, $e_3(x'_3,y'_3)$, $e_4(x'_4,y'_4)$, as shown in Figure 8. Then, a 3x3 transformation matrix containing 8 coefficients of t_{11}, t_{12}, t_{13}, t_{21}, t_{22}, t_{23}, t_{31}, t_{32} and 1 can be calculated by [11]

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1x'_1 & -y_1x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1y'_1 & -y_1y'_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2x'_2 & -y_2x'_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2y'_2 & -y_2y'_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3x'_3 & -y_3x'_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3y'_3 & -y_3y'_3 \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4x'_4 & -y_4x'_4 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4y'_4 & -y_4y'_4 \end{bmatrix} \begin{bmatrix} t_{11} \\ t_{12} \\ t_{13} \\ t_{21} \\ t_{22} \\ t_{23} \\ t_{31} \\ t_{32} \end{bmatrix} = \begin{bmatrix} x'_1 \\ y'_1 \\ x'_2 \\ y'_2 \\ x'_3 \\ y'_3 \\ x'_4 \\ y'_4 \end{bmatrix}. \tag{4}$$

Once the transformation matrix is calculated, the BMP can be warped into a region in real image by

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \frac{\begin{bmatrix} t_{11} & t_{12} & t_{13} \\ t_{21} & t_{22} & t_{23} \\ t_{31} & t_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}{\begin{bmatrix} t_{31} & t_{32} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}. \tag{5}$$

The warped makeup region represents an area in which the pixels in the area will be modified in the following steps. As a result, a binary region mask will be generated, in which the 'white' pixel indicates the pixel of the block of the input face should be modified, as illustrated in Figure 9. The warping correction obtains more accurate pattern stitching.

Figure 8. Keypoints selected in pattern warping

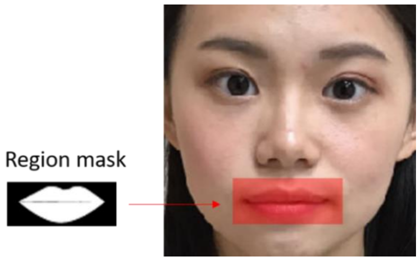


Figure 9. The illustration of region mask

The selection of keypoints is important as it affects the warping performance. We select the landmarks which are uniform distributed geometrically in the markup region. Figure 8 displays the keypoints we selected for four markup regions including eyebrows, eyes, mouth and cheeks.

2.2.3 Pattern Coloring

In this step, the best-match pattern obtained in the previous step is painted with the color selected by the user. Because most of the texture information of the pattern image can be reserved in the luminance channel, we perform the coloring only in the Chroma channel. More specifically, the input RGB face image is first converted into HSV color space. Then the V component is kept unchanged and the H and S components of the pattern are changed to the color of user's preference. The unchanged V component and the modified H and S components are converted back to RGB color space. Figure 10 illustrates the pattern coloring using the desired color of the user. It is seen that the luminance and texture of the mouth part are not changed after coloring.

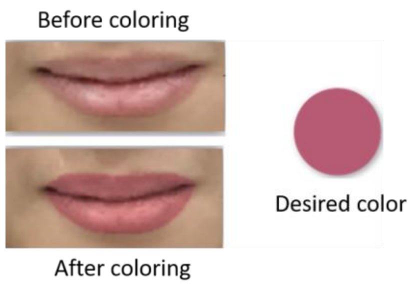


Figure 10. The illustration of pattern coloring

2.2.4 Pattern Stitching

The final step is to stich the colored pattern to an appropriate area of the input face image. The stitched area is defined according to the region mask from the previous step. The stitching may result in artificial edges on the boundaries. Thus, we apply the feathering technique to solve the problem [10]. The technique adds the colored pattern image (im_1) to input image to be pasted (im_2) with a weight factor α as

$$im_3 = \alpha \cdot im_1 + (1 - \alpha) \cdot im_2 \quad \textbf{(6)}$$

The weight α is calculated as a distance from the image edge. Figure 11 displays an example of lip stitching.

Figure 11. A demonstration of lip stitching

3 Results and Discussion

3.1 User Interface

Figure 12 shows the flow of our proposed virtual makeup system from user's perspective. The system starts from the picture selection from a disk or camera. Automatic face detection and facial landmarks detection are first performed. Then, the user selects a region for makeup. Next, the user can select color from a predefined cosmetic colors, as shown in Figure 13, or change H and/or S to make a color she (or he) likes as displayed in Figure 14. Finally, the pictures before/after makeup are saved to the storage.

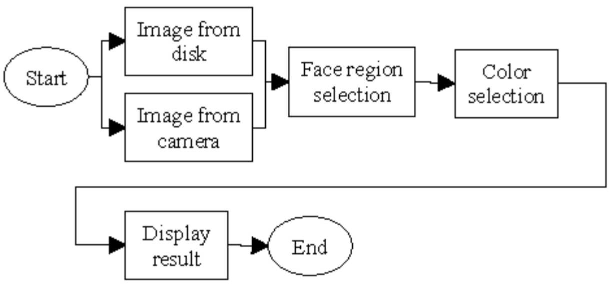


Figure 12. Proposed virtual makeup system from user's perspective

Based on the designed interface, users can adjust the shade and color of makeup. For the eyebrows, they can freely choose their favorite eyebrow shape to achieve more diverse effects. Because this system can process dynamic images from the camera, users can quickly observe the suitability of virtual makeup under different facial poses and then make appropriate adjustments of makeup accordingly.

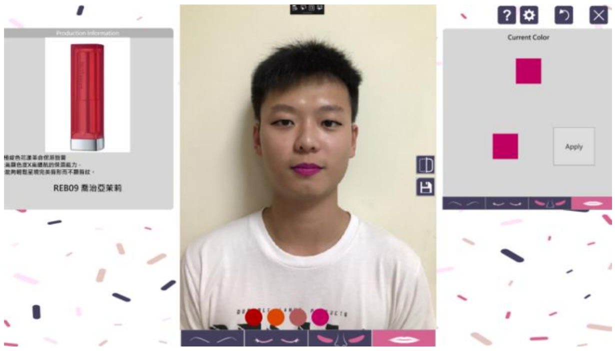
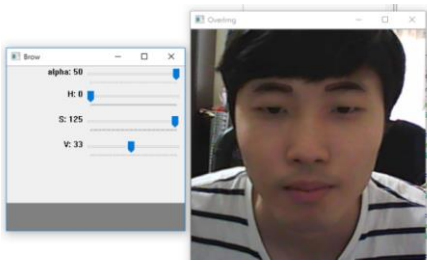
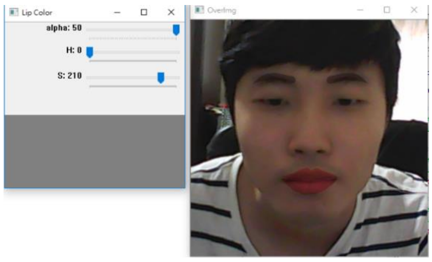


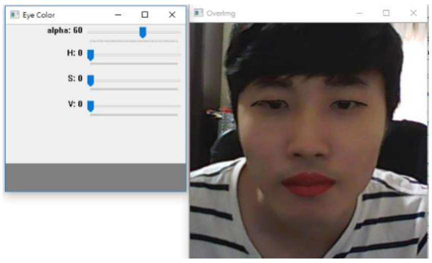
Figure 13. User interface for color selection from cosmetic color list



(a) Make eyebrow color



(b) Make lip color



(c) Make eyeliner color

Figure 14. User interface for color changes with H and S

3.2 Results and Discussion

Figure 15 displays several markup examples with our proposed system. It is seen that the makeup regions fit well for different people with different shapes of mouths. The golden-sample database provides a variety of makeup information. For example, it provides several shapes of eyebrow patterns, as shown in Figure 16. In addition, Figure 17 indicates that the makeup results look natural even poses of face or facial components vary. In summary, there are no obvious artificial edges on the boundaries of facial components. The visual effect looks much natural and harmonious. However, by magnifying the facial components, a little bit of zigzag artifacts on eyeliner can be found, as marked by an arrow in Figure 18. This will be investigated in the future.

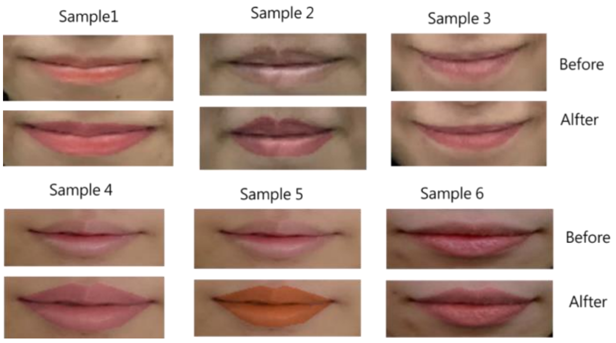


Figure 15. Makeup examples for different people

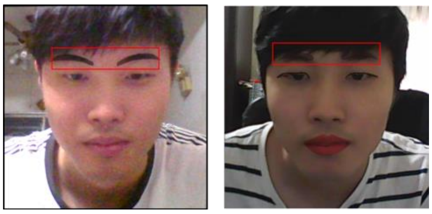


Figure 16. Makeup results with different shapes of eyebrows

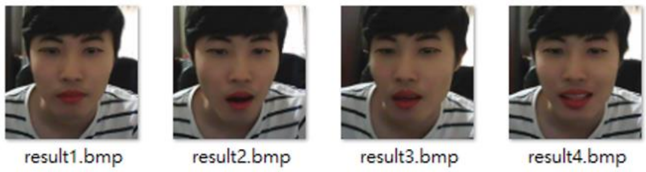


Figure 17. Makeup examples under different poses

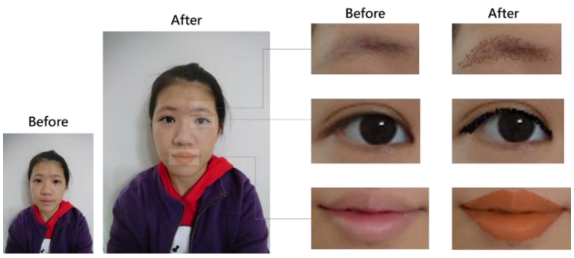


Figure 18. A little bit of zigzag artifacts on eyeliner

3.3 Method Comparison

Here, we compare our proposed method with the methods presented in [1-7] in terms of the attribute of the techniques used. We analyze the existing methods and summarize them into three categories according to makeup characteristics listed in Table 1. Category I containing [1-2] is the simplest scheme in which the makeup region is segmented out and then color tuning is applied on these regions. [3-5] belong to Category II, which performs the color and texture transfers from an example face to the user's face to implement makeup effects. Because the makeup synthesis works on the whole face, makeup part selection is not available and color tuning is limited by the example face. Our proposed method and [6-7] are Category III and have the most degrees of freedom in all aspects as they provide the ability of individual facial-part processing. As a result, the methods of Category III may yield better makeup effects in color, texture and shape.

Table 1. Three categories of virtual makeup

Category	Methods	Example transfer	Face color tuning	Facial part selection	Makeup effect
I	[1-2]	none	available	none	color
II	[3-5]	available	limited	none	color, texture
III	[6-7], Our proposed	available	available	available	color, texture, shape

We make comparison for the methods in [1-7] and our method in terms of four techniques used, as listed in Table 2. In facial part location, [1-2] use skin color segmentation and all of the rest use landmark detection to improve performance. [3-5] apply the whole face of the example image to transfer makeup skin detail and color information to the subject face. On the other hand, [6-7] and our method provides the flexibility to freely select facial parts for makeup from an example database. Differing from example matching with color feature in [6-7], our proposed method uses shape feature for example searching in the database. The shape matching can adapt to the shape variation of makeup parts of different users. In makeup synthesis, [1-2] simply tune color in makeup regions, and [3-5] compose multiple layers of the whole face. Being more sophisticated, our proposed method and [6-7] performs example stitching.

Table 2. Technique attribute comparison of various methods

	[1-2]	[3-5]	[6-7]	Our proposed
Facial part localization	Skin color segmentatic	Landmark detection	Landmark detection	Landmark detection
Makeup example	None	Whole face	Facial parts	Facial parts
Example matching	None	None	Color feature	Shape feature
Makeup Synthesis	Tuning color	Layer compositioı	Example stitching	Example stitching

4 Conclusions

The paper has presented a virtual makeup system based on golden sample search. In off-line phase, we collect facial patterns from 30 face images to create a database of golden samples. In on-line phase, a face image inputs and chosen cosmetic color is put on the makeup regions. We employ a facial landmark detector cooperating with our proposed feature representation scheme to search the best-matching pattern effectively and efficiently. Through subsequent delicate warping, coloring and stitching, a complete virtual makeup system has been built up. The system can process dynamic images from the camera, hence users can observe the suitability of makeup results under different facial poses and then make appropriate adjustments of makeup accordingly. The experimental results indicate good visual effects for users' makeup are obtained.

Acknowledgment

This work was supported in part by Fujian University of Technology, Granted GY-Z18180 and Fujian Provincial Education Department Granted GY-Z19004.

References

[1] A. Dhall, G. Sharma, R. Bhatt, G. M. Khan, Adaptive Digital Makeup, *2009, 5th International Symposium Advances in Visual Computing (ISVC),* Las Vegas, NV, USA, 2009.

[2] G. Y. Oztel, S. Kazan, Virtual Makeup Application Using Image Processing Methods, *International Journal of Scientific Engineering and Applied Science (IJSEAS)*, Vol. 1, No 5, pp.60-67, August, 2015.

[3] D. Dong, T. Sim, Digital Face Makeup by Example, *2009 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Miami, USA, 2009.

[4] L. Xu, Y. Du, Y. Zhang, An Automatic Framework for Example-Based Virtual Makeup, *2013 IEEE International Conference on Image Processing (ICIP)*, Melbourne, Australia, 2013.

[5] J.-Y. Lee, H.-B. Kang, A New Digital Face Makeup Method, *2016 IEEE International Conference on Consumer Electronics (ICCE)*, Las Vegas, NV, USA, 2016.

[6] J. Park, H. Kim, S. Ji, E. Hwang, An automatic virtual makeup scheme based on personal color analysis, *12th International Conference on Ubiquitous Information Management and Communication (ICUIMC)*, Langkawi, Malaysia 2018.

[7] T. Alashkar, S. Jiang, S Wang, Y Fu, Examples-Rules Guided Deep Neural Network for Makeup Recommendation, *31th AAAI Conference on Artificial Intelligence (AAAI-17)*, San Francisco, USA, 2017.

[8] D. E. King, Dlib-ml: A Machine Learning Toolkit, *Journal of Machine Learning Research*, Vol. 10, No. 3, pp. 1755-1758, 2009.

[9] N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, San Diego, USA, 2005, pp.886-893.

[10] R. J. Locke, R. J. Edens, P. R. Barber, B. Vojnovic, An Algorithm for Image Stitching and Blending, Proceedings of SPIE, Vol. 5701, pp.190-199, March 2005.

[11] R. I. Hartley, A. Zisserman, *Multiple View Geometry in Computer Vision 2nd Edition*, Cambridge University Press, 2004.

Biographies

Ping Wang was born in Fuzhou City, China, in July 1984. She received the Master in software engineering from Fuzhou University in 2012. She is an experienced senior engineer in big data development and application. Her research interests include deep learning, graphics and image processing, big data and Internet of Things.

Mao-Hsiung Hung received the M.S. degree and Ph.D in information engineering from the I-Shou University, Taiwan, in 1999 and in 2009 respectively. He is currently an associate professor in the School of Computer Science and Mathematics at Fujian University of Technology, Fuzhou, China. His research interests include image processing and machine learning.

Chaur-Heh Hsieh received Ph.D. degree in Electrical Engineering in 1990 from Chung Cheng Institute of Technology (CCIT), Taiwan, Republic of China. In 1981, He joined the faculty of the Department of Electrical Engineering at CCIT, and became a professor in 1993. From 1996 he joined I-Shou University (ISU) as a full professor of Information Engineering Department. From 1999 to 2002, he served as the chairman of the department. He was a Visiting Scholar in the Department of Electrical Engineering at University of Washington from February to July in 2006. From 2007 to 2018, he was a Professor with Ming-Chuan University. He is currently a Professor of College of Artificial Intelligence, Yango University, Fuzhou, China. His current research interests include signal and image processing, computer vision, and deep learning. He is an IET Fellow.

Jen-Yang Chen received the M.S. degree in electrical engineering from the Tatung University, Taipei, Taiwan, R.O.C., in 1992 and the Ph.D. in electrical engineering from Tamkang University, in 2000. He is currently a full professor in the Department of Electronic Engineering at Ming Chuan University. His research interests include deep learning and intelligent control.