Automatic Detection and Correction for Glossy Reflections in Digital Photograph

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Abstract— **The popularization of digital technology has made shooting digital photos and using related applications a part of daily life. However, the use of flash, to compensate for low atmospheric lighting, often leads to overexposure or glossy reflections. This study proposes an auto-detection and inpainting technique to correct overexposed faces in digital photography. This algorithm segments the skin color in the photo as well as uses face detection and capturing to determine candidate bright spots on the face. Based on the statistical analysis of color brightness and filtering, the bright spots are identified. Finally, bright spots are corrected through inpainting technology. From the experimental results, this study demonstrates the high accuracy and efficiency of the method.**

Index Terms— **Glossy reflection, Oily face, Skin detection, Face detection, Digital inpainting, Digital photography.**

I. Introduction

Digital cameras have become very popular in recent years because of their portability and multipurpose functionality. However, red-eye, oily face and glossy reflections often occur under low light conditions when a camera flash is used. Some photo-editing software applications (such as Adobe Photoshop or Photoimpact) have provided tools for the reduction of oily face and glossy reflections, but most of them require considerable user interactions.

This paper intends to propose an unsupervised technique using low-level image features to locate the glossy reflection per-pixel in a digital photo and thereby eliminating the need to detect the face and/or skin regions in an image. Another advantage of the approach is to limit the processing of illumination, since the oily face phenomenon is a direct result of flash use. Therefore, the computational overhead is reduced considerably. Basic processing techniques, such as median filtering and morphological operations, as well as skin color and shape-based constraints, are utilized in repeat and in succession to reduce the number of candidate regions that may correspond to glossy reflection. Furthermore, each component of the image color space is analyzed separately and the results are merged to yield a more reliable output. Based on these concepts, the rest of this paper is organized as follows: Section II discusses the background to the specularity removal and oily face correction problems. Section III describes the proposed algorithm. Section IV presents the detection and correction of our experimental results and analysis. Conclusions and future work are described in Section V.

II. Related Work

A number of previous works have been done in the field of image processing. Tan *et al*. [1] proposes highlight removal method without performing color segmentation and using polarization filter. This method produces specular-free image devoid of specular effect but retains exact geometrical information; however a shift in color value can be spotted. By using logarithmic differentiation between specular-free image and input image, the highlight-free pixels are successfully detected. Then the specular component of each pixel is removed locally involving a maximum of only two pixels. Tan's method is also suitable for multicolored texture images. While Tan *et al*. successfully dealt with the problems of color segmentation, a drawback of their method is the requirement of detecting local color discontinuities. Once the method fails to detect a significant number of discontinuities, the end results will tend to be erroneous. To overcome the problem, paper [2] introduces a method using global approaches instead of local ones. The method principally utilizes the coefficients of the reflectance basis functions of input image and its specular-free image. Combining those coefficients enables us to find the diffuse coefficients of the specular pixels for every surface color.

Based on color analysis and multi-baseline stereo, Lin *et al.* [3] introduced a method that simultaneously separates the diffuse and specular reflections and estimates the true depth. This proposed method can identify specular pixels by a voting-based multiple tri-view color histogram differencing. Mallick *et. al.* [4] then presented an SUV color space by separating the specular and diffuse components into S channel and UV channels. The SUV color space can be used for highlight removal through a single image or video sequences, but this method cannot make the diffuse information accurately propagated because of the discontinuities in surface colors. Therefore, Shen and Cai [5] further proposed a highlight removal method employing a modified "pseudo-coded" diffuse image. This method is used only for multi-color surfaces when the dominant highlight region is approximately uniform.

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In addition, specific methods have been proposed in the literature for detecting and/or removing red-eye or face oily artifacts [6][7]. Most of these methods are either (1) supervised, i.e. they require the user to manually identify the sub-regions in an image where the artifacts are observed, or (2) dependent on skin /face detection to find the areas of interest.

Different environmental illumination has a great impact on face detection and recognition. Automatic detection and radiant correction of highlighted region on face image is helpful to identify human faces correctly in a color image. Chen *et. al.* [8] present a novel approach based on dichromatic reflection model to detect and remove highlight in face region. They employed a highlight analysis on a critical two-dimensional chromatic plane (TSL color model) and a stepwise PCA to automatically detect the existence of highlighted face regions. The proposed approach estimates the skin dichromatic reflection vectors, by which highlight in face region can be removed.

III. The Proposed Method

This section explains the proposed automatic detection of overexposed face regions and inpainting algorithms. In order to effectively detect bright spots and perform color correction in color photos, this study proposes an integration of different algorithms to obtain highlight information, followed by inpainting techniques for corrections. Figure 1 illustrates the flowchart of the proposed method.

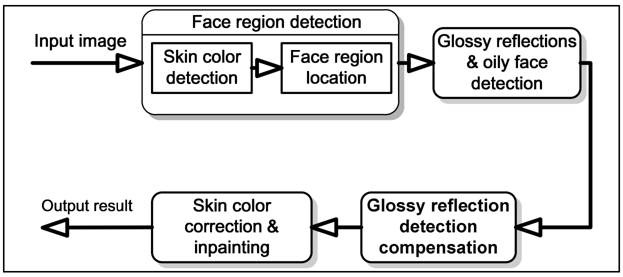


Figure 1. The block diagram of the rough detection and correction methods.

This experiment involves a number of major steps, described as follows:

(1) *Input image*: User inputs one or more color photos containing overexposed face regions.

(2) *Face region detection*: This step consists of skin color detection and face region detection, which aim to find the region of interest through color detection and filtering of human skin characteristics; ellipse detecting technique is then used for face detection. The skin color parameter in this present study is designed for Asian skin color that tends toward yellow.

(3) *Glossy reflection and oily face detection*: After the face region is confirmed, the YC_bC_r color space is used to calculate changes in the brightness of the face, and the dynamic threshold value is determined to search for potential candidate regions for marking.

(4) *Glossy reflection detection compensation*: Using filters in the candidate region could filter out false marks to give the real regions in need of inpainting.

(5) *Skin color correction and inpainting*: Face color correction or inpainting can be achieved through digital techniques. This step targets each of the pixels to be inpainted and uses adjacent mask search and matching to find the best color pixels and correct the overexposed pixels.

(6) *Output image*: After inpainting, a new color photo is produced, where the overexposed bright spots on the face are color corrected and inpainted.

A. Face region detection

The framework of the *face region detection* method comprises two main components: *skin color detection* and *face region location* discussed as follows.

Skin color detection

Skin color detection techniques are widely used in the detection and tracking of body parts in images or video, with applications ranging from the detection and tracking of face region, body area, gestures, and character recognition in databases or on the Internet. The main purpose of skin color detection or classification is to establish a decision rule to determine the skin and non-skin color pixels. Identification of skin color relies on the finding of color pixel value range in an appropriate color space, where a good skin color model must have a high detection rate and low error rate. In general, skin color pixel range can be attained through skin detection algorithms [9][10].

Skin color has its characteristics, which can form different expressions in different color spaces. Therefore, different skin color identification abilities and treatment effect are required for different color spaces. Common color spaces are RGB, CMY/CMYK, YC_bC_r, HIS (HSV), YIQ, YUV.

This paper describes the skin color model with YC_bC_r color space, since it is similar and resembles human's visual perception that separates brightness and chroma very well. In addition, the YC_bC_r color space is discrete, which makes it easier to perform clustering algorithm.

YC_bC_r was developed as part of the ITU-R Recommendation B.T. 601 digital video standards and television transmissions. In YC_bC_r, the *RGB* components are separated into luminance (Y), chrominance blue (C_b) and chrominance red (C_r). The Y component has 220 levels ranging from 16 to 235, while the C_b, C_r components have 255 levels ranging from 16 to 240. YC_bC_r color space has the following advantages:

(1) Its principle is similar to the process of human visual perception.

(2) Space format of YC_bC_r color room is widely used in the television display area. It is also used in video compression coding, such as MPEG, JPEG.

(3) Its space format separates brightness component from the color components.

(4) Its space format's calculation process and representation of spatial coordinates are easier than others.

The conversion formula from the RGB space to the YC_bC_r space is as follows:

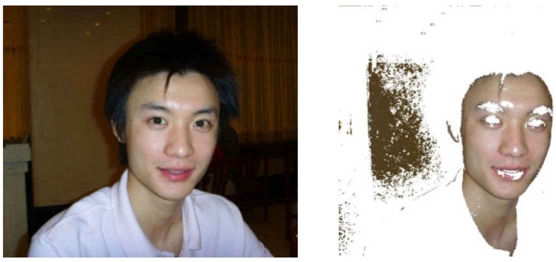
$$\begin{bmatrix} Y \\ C_b \\ C_r \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \quad (1)$$

In contrast to RGB, YC_bC_r color space is a luminance-based color model, providing a more efficient calculation method for skin color analysis. Concerning color clustering, we make reference to the suggested value for skin color range as proposed by Kukharev *et al.* [11], as follows.

$$\begin{aligned} &60 \leqq Y \leqq 250 \\ &90 \leqq Cb \leqq 135 \\ &135 \leqq Cr \leqq 170 \end{aligned} \quad (2)$$

where Y, C_b, C_r =[0, 255].

In this experiment, test subjects are of the yellow race, i.e. Asian skin tone. Based on calculations of skin color range, non-skin color pixels are set to be white color, giving the experimental results shown in Figure 2 (b). The obtained new images are designated as *candidate face regions*.



(a) (b)

Figure 2. Example of skin color segmentation: (a) original image, (b) results of skin color detection.

Face region location

Since the identified *candidate face regions* may be actually parts of the human body, such as hands, other than faces, further verification should be performed to locate the real face regions. Two steps as explained below are used in our verification process.

Step 1: For a given gray scale image, find out the edge image using suitable edge detection operators

To obtain the edge information on the objects in the photo, morphological imaging procedures are utilized to transform color images into grayscale images. Next, threshold processing technique converts the gray-scale images into binary images. Since the threshold for each grayscale image conversion into binary image is not fixed, Otsu algorithm is used [12], a pixel information statistical method, to automatically calculate the best threshold value as follows:

Assume the grayscale range from 1~L, and the cumulative pixel of each gray scale is n_1, n_2, n_3,…, n_L, respectively, and with the total pixels being N, then the occurrence probability of gray level i would be calculated as formula (3):

$$P_i = \frac{n_i}{N},\ P_i \geq 0,\ \sum_{i=1}^{L} P_i = 1 \quad (3)$$

Let C_0 denotes the cluster of grayscale 1~k, C_1 the cluster of grayscale k+1~L, w_0 and w_1 the occurrence probability for C_0 and C_1, respectively, and μ_0 and μ_1 the mean of C_0 and C_1, respectively. The calculations are as follows.

$$w_0 = \sum_{i=1}^{k} P_i = w(k) \quad (4)$$

$$w_1 = \sum_{i=k+1}^{L} P_i = 1 - w(k) \quad (5)$$

$$\mu_0 = \sum_{i=1}^{k} \frac{iP_i}{w_0} = \frac{\mu(k)}{w(k)} \quad (6)$$

$$\mu_1 = \sum_{i=k+1}^{L} \frac{iP_i}{w_0} = \frac{\mu_T - \mu(k)}{1 - w(k)} \quad (7)$$

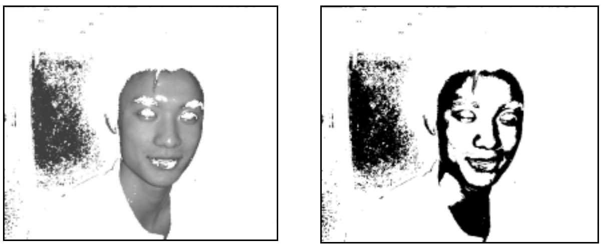
The variance of each cluster, σ_0^2, σ_1^2, and the sum of the variance, α_w^2 are:

$$\sigma_0^2 = \sum_{i=1}^{k} (i - \mu_0)^2 \frac{P_i}{w_0} \quad (8)$$

$$\sigma_1^2 = \sum_{i=k+1}^{L} (i - \mu_1)^2 \frac{P_i}{w_1} \quad (9)$$

$$\sigma_w^2(k) = w_0\sigma_0^2(k) + w_1\sigma_1^2(k) \quad (10)$$

When the Otsu algorithm finds a k value that gives the smallest possible sum of variance, this k value is deemed as the best threshold. The threshold calculated using this method outperforms the use of a fixed threshold value. The post-processed results are shown in Figure 3.



(a) (b)

Figure 3. The example of segmented face regions: (a) gray-level image, (b) binary image.

Noise is detected in the binary image in Figure 3 (b). Noise reduction can be achieved using dilation and erosion operations. Since an image usually contains multiple objects, edges are important features. To differentiate two objects, neighboring pixel variations can be used to determine the edges, where large neighboring pixel discrepancies often signify the edge of an object.

Through noise filter, dilation and erosion operations, preliminary face candidate regions are obtained. For more accurate edge information of the object, Sobel edge detection is utilized to enhance computational efficiency [13]. Sobel operator consists of a pair 3×3 convolution kernels as shown in Figure 4.

-1	**0**	**+1**
-2	**0**	**+2**
-1	**0**	**+1**

-1	**-2**	**-1**
0	**0**	**0**
+1	**+2**	**+1**

Figure 4. Sobel convolution kernels.

These kernels are designed to respond maximally to edges running horizontally and vertically relative to the pixel grid. If we define S as the source image, and G_x and G_y are two images which at each point contain the horizontally and vertically derivative approximations, the computations are as follows:

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} * S \quad \text{and} \quad G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} * S \tag{11}$$

where $*$ here denotes the 2-D convolution operation.

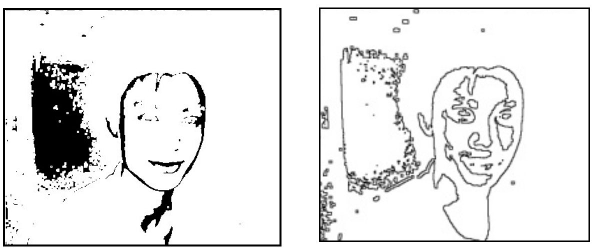
At each point in the image, the resulting gradient approximations can be combined to give the gradient magnitude, using:

$$G = \sqrt{G_x^2 + G_y^2} \tag{12}$$

Using this information, we can also calculate the gradient's direction:

$$\Theta = \arctan\left(\frac{G_y}{G_x}\right) \tag{13}$$

The Figure 5 is an example result using this edge detection method.



(a) (b)

Figure 5. Example of Sobel edge crispening: (a) noise removal, and (b) edge crispening.

Step 2: Using the elliptical template to find out the face area.

Elliptical-shape is one of the characteristics used in human face recognition. This method uses pre-constructed elliptical template, and detects the edges of the candidate face region to find the location of possible ellipses. The elliptical template is constructed based on the 1:1.2 ratio of the major and minor axes of the ellipse, where the length and width ratio is spatially resized along the edge of the lines repeatedly in search of the optimal face region. The formula (14) is as follows:

$$\frac{x^2}{(1.2b)^2} + \frac{y^2}{b^2} = 1, \tag{14}$$

In formula (14), $1.2b$ is expressed as the elliptical major axis, b as the elliptical minor axis, O as the origin (x_0, y_0), and p as any given point on the ellipse. The search space is defined as formula (15):

$$S = \{S \mid |x - x_0| \le x_r, |y - y_0| \le y_r|, |b - b_0| \le b_r\}, \tag{15}$$

where x_r and y_r denote the search region at point (x_0, y_0), b_0 the radius of the minor axis, and b_r the search region within the radius of the elliptical minor axis.

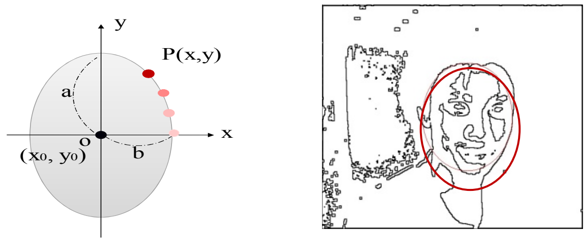
Ellipse detection mainly calculates grayscale gradient distribution on the elliptical mask, and more indicates it is closer to an ellipse, thus more likely to be a human face. The ellipse center (x_0, y_0) is used to calculate all the coordinates (x_0, y_0) on the circumference, as presented in formula (16):

$$\begin{cases} x_0 = x_0 + x\cos(\theta) \\ y_0 = y_0 + y\sin(\theta) \end{cases}, \theta = 0^0 \sim 360^0, \tag{16}$$

Summation of the gray gradient values of the circumference is divided by the perimeter, and the pixel counts contained on the circumference are calculated to obtain the average gradient of the elliptical circumference, as in formula (17):

$$\overline{G}(s) = \frac{1}{n_b}\sum_{i=1}^{n_b} |g(i)|, \tag{17}$$

where n_b represents the pixel count on the elliptical circumference, $g(i)$ the gradient value of the i^{th} pixel on the ellipse, and $\overline{G}(s)$ the similarity to an ellipse, in which higher value means it is closer to an ellipse. The Figure 6 is an example result using this elliptical template to find out the face area.



(a) (b)

Figure 6. An elliptical position map of facial features, (a) an elliptical template; (b) the face region.

B. Glossy reflection and oily face detection

After the skin color range identification and face recognition, the human face region is acquired for follow-up bright spot detection and image inpainting. According to our experiment and observation, overexposed bright spots on the face generally have two characteristics:

(1) they are close to white in color

(2) they always appear within the skin color range

Here, Y value of the YC_bC_r color space is used to detect gray-scale brightness in the image for the purpose of establishing a threshold value of α = (maximum brightness value – minimum brightness value)×80%. When the brightness of pixel p is less than α, it is not a target bright spot. If it is more than α, further calculation is needed to confirm whether it is within the skin color range; and if it is, pixel p is considered a target bright spot. When the pixel is not inside the skin color range, a 3×3 adjacent mask is used for filtering; if the pixel in this mask is within the skin color range, pixel p is a candidate bright spot. This approach ensures that no bright spots are missed, since the bright spot pixel value is close to white color. The following algorithm 1 is implemented to determine candidate bright spots area.

Algorithm 1: Determining candidate bright spots area

Input: a human face image
Output: candidate bright spots area

B_{Max} : maximum brightness value
B_{Min} : minimum brightness value
α: a threshold value, α=(B_{Max} - B_{Min}) × 0.8

for each image pixels P {
  if ($P_{(y,x)}$' gray vale $>\alpha$ AND $P_{(y,x)}$ in the skin color scope)
    $P_{(y,x)}$ is candidate bright spots area;
  else if ($P_{(y,x)}$ in the 3×3 adjacent mask while the skin color scope > 1/3)
    $P_{(y,x)}$ is candidate bright spots area;
  else $P_{(y, x)}$ not candidate bright spots area
}

(a) (b)

Figure 7. Candidate bright spots area detection (a) test image, (b) detection result.

C. Glossy reflection detection compensation

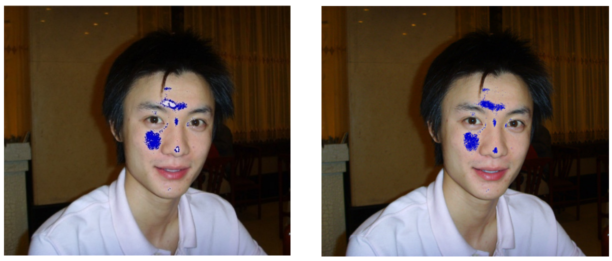
In Figure 7 (b), the blue pixels represent the candidate bright spots area, and even though the area is small, bright pixels are still observed and adjacent pixel values also tend toward white. If the overexposed bright spot area is too large, omission in bright spots detection may occur; as a result, compensation algorithm for overexposed bright spot detection is required to obtain the correct bright spot area. First, a target threshold β is set for the number of target bright spots. If the pixel brightness value is greater than α, and the number of target bright spots in the 3×3 adjacent mask exceeds β, then this pixel will be considered as a target bright spot. The compensation outcomes from algorithm 2 are presented in Figure 8 (b).

Algorithm 2: Filtering candidate bright spots area

Input: candidate bright spots area
Output: target bright spots area

β: a threshold value,

for each image pixels P {
  if ($P_{(y,x)}$' gray vale $>\alpha$)
    if ($P_{(y,x)}$ in the 3×3 adjacent mask while the number of candidate bright spots area $>\beta$);
      $P_{(y,x)}$ is target bright spots area;
    else $P_{(y,x)}$ is not the target bright spots area;
  else $P_{(y,x)}$ is not the target bright spots area;
}



(a) (b)

Figure 8. Example of glossy reflection compensated (a) the test image, (b) the compensated result.

D. Skin color correction and inpainting

This section explains the process of skin color inpainting in target bright spots.

Digital inpainting is a technique which restores damaged image or video by means of spatial / temporal interpolation and other mechanisms. The technique can be used in photo restoration. Current techniques are based on extrapolation or interpolation of neighboring pixels [14], recovery of edges, curvature-driven diffusions (according to the connectivity principle in vision psychology) [15], and inpainting from multiple view points (*i.e.*, image from movie, or image from different time and view point). In this study, we present an inpainting process that is based on color mathematical morphology, as a traditional inpainting which propagates boundary values.

Image inpainting often uses adjacent information to perform the task for the target region. However, if the inpainting sequence is carried out in a horizontal direction (e.g. from left to right), a diffusion of inpainting information to the right may occur. To avoid this problem, the overexposed bright regions are divided into edges and the interior, where the inpainting process starts around the edges and layer-wise move into the interior to prevent the diffusion of inpainting information along a particular direction.

To obtain the overexposed edges and the interior, we designed a cross mask, as shown in Figure 9. Suppose pixel P is a target bright spot, and any of the a, b, c, or d points is not a target bright spot, then point P is on the edge of the bright spot; in reverse, point P is the interior of the bright spot. The detection results are shown in Figure 10, where the blue pixels denote bright spot edges and red pixels the interior.

Suppose point P is the boundary of a target bright spot, a 3×3 adjacent mask is used to search for skin color range and non-target bright spot pixels. The search results are temporarily stored to array a and sequenced based on the brightness Y values in a descending order. The YC_bC_r pixel value of the median of array a is then utilized for skin color inpainting as shows in algorithm 3.

	a	
d	P	b
	c	

Figure 9. The 3×3 cross mask.

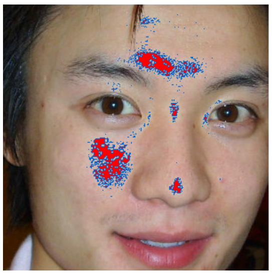


Figure 10. Example of detection result for skin color inpainting.

Algorithm 3: skin color inpainting

Input: the original image
Output: the repaired image

for each image pixels P {
if (the $P_{(y,x)}$ is the surrounding of target bright area)
then search the 3×3 adjacent mask of $P_{(y,x)}$
if the surrounding pixels are not the bright spots but they are in the skin color area
then copy the brightness value of $P_{(y,x)}$ to array Light[t];
To obtain the intermediate values of Light[t] and inpainted the $P_{(y,x)}$;
}

For the inpainted bright-spot areas to be rendered naturally in terms of visual impression, inpainted pixels are further evaluated. Suppose the intensity value of the inpainted pixel is greater than the threshold value γ, the skin color of this pixel is adjusted. The threshold value γ is the addition of threshold α and parameter k, where k is an increment to avoid skin color inpainting values from having to become brighter outwardly in the inpainting process.

IV. Experiment Results and Analysis

This section presents the face highlight detection and inpainting strategies using actual photos for experiments and analysis, and discusses the experimental results.

A. Preliminary Examples

Here, 35 digital photographs with bright spots on the face region were used. Obtained from the Internet or from actual portrait shots, the over-exposed facial highlights and portrait background in each photo varied to different degrees for examination of the adaptability of our method.

Figure 11 shows the results of the glossy reflections correction. Figure 11 (a) presents the original images and Figure 11 (b) illustrates the recovered images. Enlarged images shown in Figure 12 demonstrate the detailed experimental results. Through the proposed methods, the glossy reflections and oily skin can easily be detected. Furthermore, the true color of the target area can be restored by using color information of human skin colors.

#1
#2
#3

#4

(a) (b)

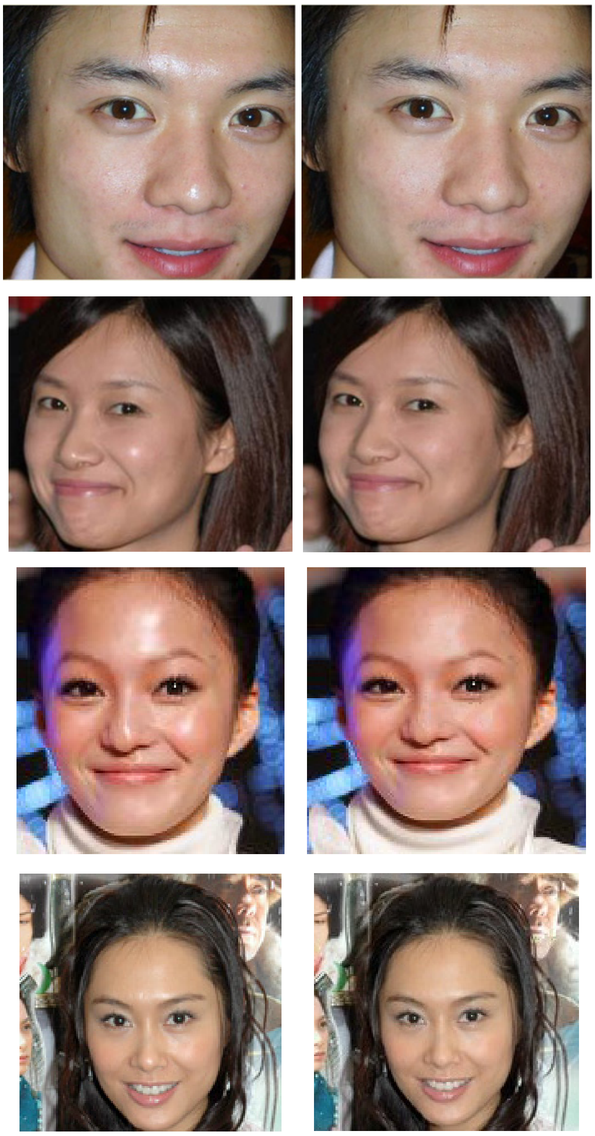
Figure 11. The experiment results of sample photos: (a) original images, and (b) results of our proposed method.

#1

#2

#3

#4



(a) (b)

Figure 12. The experiment results enlargement from Figure 11: (a) the original images, and (b) the results.

B. *Comparison and Analysis*

Koirala *et al*. [16] exploited principal component analysis (PCA), histogram equalization and second order polynomial transformation to successfully remove the bright spots in images, some of which are targeted at removing highlights from portraits. Figure 13 illustrates a comparison between the results of our proposed method and that of Koirala *et al*., with the original photograph in Figure 13 (a), Koirala's results in Figure 13 (b), and our results in Figure 13 (c). We observed from the comparison that although Koirala's methods successfully removed the facial highlights, the overall portrait skin tone faded to a whiter color, while the white of the eye seemed to be dimmer, which was evidently unnatural. On the other hand, our methods allowed the retention of the original eye color, particularly the white regions, while successfully restored the facial bright spots, giving the inpainted photograph a supple tone that is natural and easy on the human visual perception.

(a) (b) (c)

Figure 13. Sample results from our algorithm and Koirala's method: (a) original photograph, (b) Koirala *et. al*, and (c) our method.

As regards the applicability of this proposed method, the algorithm considers low computational complexity and reduced computing time. In the algorithm process, image preprocessing, including color detection, gray scale manipulation, thresholding and edge detection, takes up a short amount of the time. Ellipse detection algorithm used to recognize the face area may be more time consuming, hence the design of an elliptical template 84×70 pixels (fixed proportion of 1:1.2 between the minor and major axes of the ellipse) is in place to accelerate the computing time during a face search as it automatically adjusts to find the best fitting facial contours. The reiteration of facial bright spot inpainting is controlled by the threshold value γ in inpainting strategies, which effectively enhances the post-inpainting visual effects.

Table I is an example that demonstrates the computational time and iterations of inpainting. Based on experimental results from a variety of test images, the proposed method has very low computational complexity, so it can easily implemented into a mobile camera phone or a PDA phone.

Table I.
PERFORMANCE ANALYSIS

Item	Image size (pixels)	Computing time (sec)	Inpainting iterations
#1	726×622	1.71	1
#2	550×566	1.15	1
#3	1040×660	2.20	2
#4	916×730	2.86	2

V. Conclusions

Employing digital inpainting technique under a full set of camera motions is a challenging task. This paper aims to present an effective automatic approach to detect and repair glossy reflection and oily skin. One of the major contributions of this study is to develop an automatic detection and correction procedure based on skin color face detection and a novel inpainting algorithm. Experimental results provide evidence that the proposed algorithm can produce visually pleasant results. Moreover, the proposed methods can serve as an effective add-on to existing photo editing software, maximizing users' ability to create perfect photos.

Acknowledgments

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