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Concise Papers

Using Hybrid Knowledge Engineering and Image Processing in Color Virtual Restoration of Ancient Murals

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Abstract—This paper proposes a novel scheme to virtually restore the colors of ancient murals. Our approach integrates artificial intelligence techniques with digital image processing methods. The knowledge related to the mural colors is first categorized into four types. A hybrid frame and rule-based approach is then developed to represent knowledge and to infer colors. An algorithm that takes into account color similarity and spatial proximity is developed to segment mural images. A novel color transformation method based on color histograms is finally proposed to restore the colors of murals. A number of experiments based on real images have demonstrated the validity of the proposed scheme for color restoration.

Index Terms—Mural, color restoration, hybrid reasoning, color image processing.

1 Introduction

With the development of digital image processing, the restoration and preservation of art works using digital technology has been widely accepted as an effective and practical method. In particular, the virtual preservation and restoration of paintings have attracted the interest of researchers from both the art and image processing communities. Some applications have been developed [1], [2], [8], [9] which can be used as a guide to the actual restoration of the artwork, but, in general, they are intended for clearing soiled paintings or removing cracks from old paintings and frescoes.

Mogao Grotto, located in the Dunhuang region of the Gansu province, China, has been a treasure of Chinese art and is listed as a World Heritage Site by the United Nations. Dunhuang's frescoes have a history of nearly 2,000 years. Unfortunately, due to discoloring and partial decay for various reasons, the murals have been badly damaged. Scientists and artists at the Dunhuang Research Academy of China have been working for a long time on the protection and restoration of murals by analyzing the composition of pigments through chemical experiments or by restoring colors in the process of imitating original murals. Chemical experiments, however, require collecting pigment samples from murals, which is in conflict with the protection of the art works. While restoring colors depends on the artists' personal understanding on the ancient art, a large part of their knowledge about the application of colors on murals is heuristic and has been developed over a long period of practical experience.

We have studied and developed a computer-aided system to virtually restore mural colors. Our aim is to build a bridge between the technical and art communities through which the user can utilize knowledge from the experts of various fields to restore mural colors rapidly. Such a system is not only useful for the appreciation of murals, but also provides a new approach for the artists to understand the ancient application of mural colors.

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2 Status of Discoloration of Dunhuang's Murals

2.1 Classification of Discoloration

The discoloration of murals can be categorized into two classes [3]: color fading and color change. The color fading of a pigment means the decrease of its luster and saturation or the weakening of color contrast between different pigments. It is a common phenomenon that, in Dunhuang, almost every color has faded to a certain extent. The color change of a pigment is one of the serious disfigurements because it results in one pigment's chrominance changing into others and the pigment's original bright hue becomes gloomy and vague. The internal cause of the color change is that the pigments contain lead substances, such as PbO_2 (black lead), Pb_3O_4 (red lead), and $3PbCO_3 \cdot 2Pb(OH)_2$ (white lead). It has been found that the more lead a pigment contains, the more the color changes.

2.2 Environmental Factors Causing Discoloration of the Wall Paintings

The external causes leading to mural discoloration are very complex. They include physical, chemical, and biological ones, such as sunshine, oxygen, industrial gas, temperature, humidity, mold, bactera, etc. Among these causes, sunshine, temperature, and humidity are the most important ones. The location, tier, and size of a cave roughly determines its temperature and humidity range. In the same cave, the wall paintings exposed to the sun are more seriously discolored than those not exposed to the sun.

The extent of the color change in a lead pigment is different under different environmental conditions [3]. For example, white lead under certain sunshine conditions changes its color according to the regular pattern: white $\rightarrow$ light gray $\rightarrow$ light coffee $\rightarrow$ brown coffee and the pattern of red lead is: tangerine $\rightarrow$ brown red $\rightarrow$ black red. Yellow lead under certain humidity conditions changes its color according to the regular pattern: yellow $\rightarrow$ light gray $\rightarrow$ light green $\rightarrow$ blackish green.

3 System Architecture

We develop a computer-aided system to virtually restore the colors of murals. This system integrates artificial intelligence and image processing techniques. Fig. 1 shows the system architecture.

Users interact with the system through the user interface module. The image processing module fulfills the image's segmentation, region extraction, and color restoration as well. The input and output modules are used to maintain database, knowledge base, and input/output images. The inference engine is used to determine the changed and restored colors.

3.1 Classification of the Color Restoration Knowledge

The color restoration knowledge is classified into the following four types [4]:

1. Environmental knowledge. As mentioned in the last section, environmental factors affect the extent of mural discoloration. Determining and representing these factors are important for color restoration of wall paintings. This kind of knowledge is relative to a cave's size, temperature, humidity, sunshine, position, and the like.

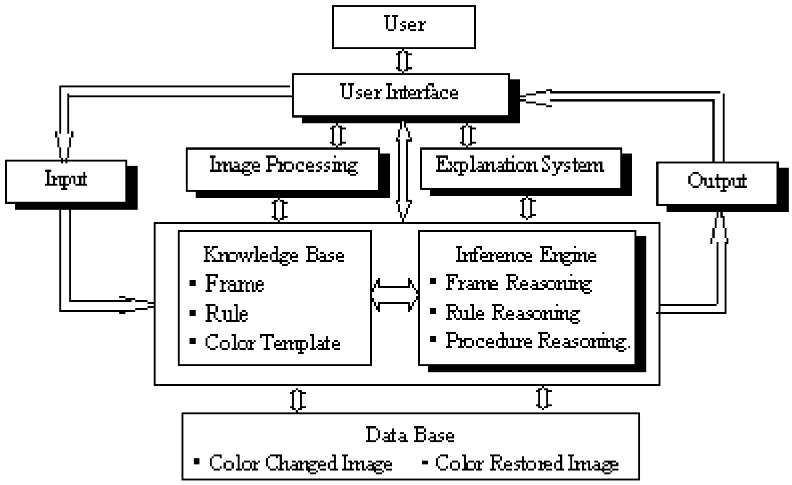


Fig. 1. System architecture.

2. Color distribution knowledge. The pigments contain mineral, phytogenic, or their mixture. Moreover, murals painted in different dynasties, ages, and caves have their own characters and certain regular patterns. So, the knowledge relative to ages and caves can roughly determine the distribution of mural colors.
3. Painting style knowledge. It contains mural topics, contents, and painting styles. For example, a faint dyeing method was widely used on people's faces to emphasize the depth.
4. Typical color templates. The researchers at the Dunhuang Art Research Academy used X-ray diffraction, infrared spectrum, SEM, and microphotograph to analyze the pigments used. Although the analysis is limited, the surveying results are usually valuable.

3.2 Representation of the Color Restoration Knowledge

As expert system technology has been widely accepted in solving symbolic reasoning-based problems, it has become increasingly apparent that no single programming paradigm is suitable for the entire solution of the problems. We thus propose combining frame and rule-based representation paradigms into a single integrated framework in order to model and infer the complicated mural discoloring phenomena.

3.2.1 Frame Representation

In the knowledge base, the frames are organized hierarchically according to the murals' contents. The top layer is composed of concepts, the middle layers are composed of the instance frames for different mural contents, and the bottom layer is composed of the instance frames for various color objects, which are the patterns with certain geometrical and physical meanings. Fig. 2 shows the hierarchical structure of the frame knowledge base, where the frames about people are listed in detail.

3.2.2 Rule Representation

For the restored murals, some frame attributes can inherit from their father frames or be retrieved from the database, whereas the restored colors are determined by rule-based reasoning. For example, for murals of the Sui dynasty, people's faces were usually painted in four main dyeing ways:

1. the integrated Chinese and western dyeing style,
2. traditional Chinese dyeing style,
3. Chinese white face, and
4. TianLi inherited style.

The production rules associated with these four painting styles can be expressed as:

R1: IF Dynasty ="SUI dynasty" and Style ="Combination of
Chinese and Western elements" and

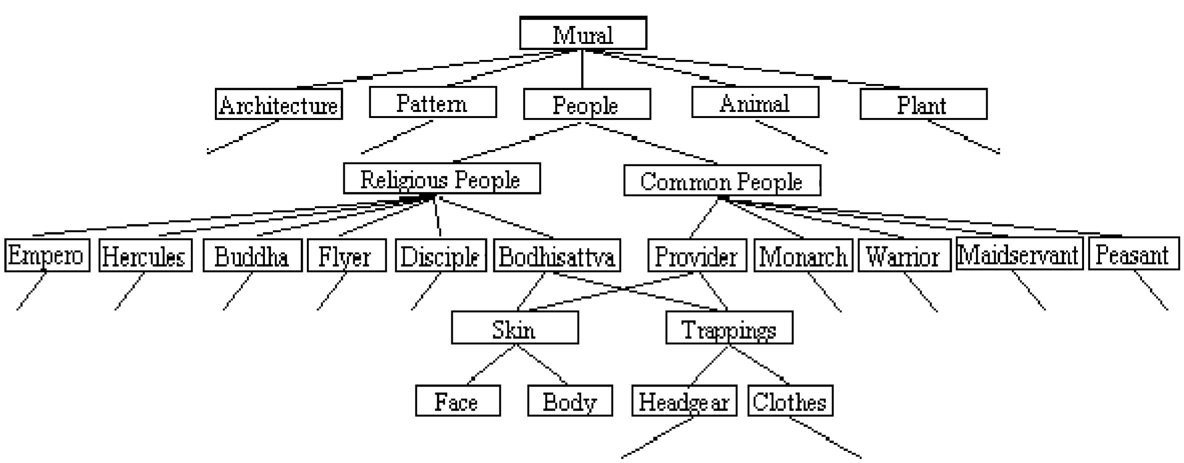


Fig. 2. Hierarchical structure of frames.

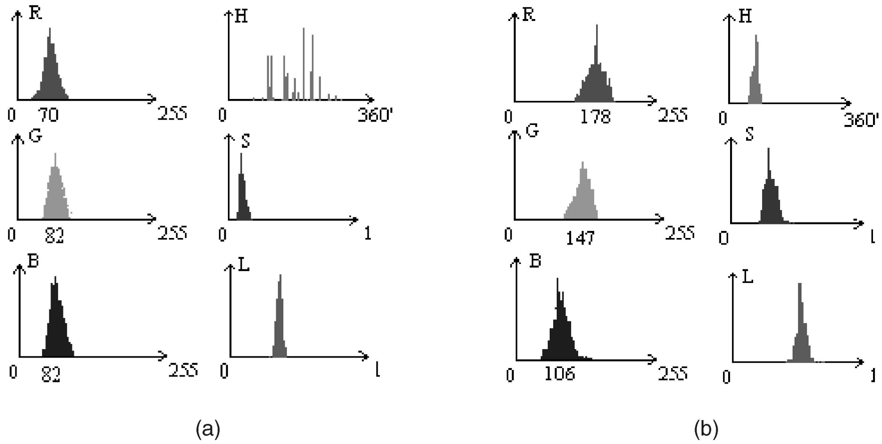


Fig. 3. Two colors distributions in RGB and HSL color spaces. (a) Divergent distribution of gray hue. (b) Regular distribution of tangerine hue.

Content =“Buddha” and C_Object =“Face”
THEN (Base_Color,Dyeing_Color)=(RGB(192,160,141), RGB(152,80,56))

R2: IF Dynasty =“ SUI dynasty” and Style =“Traditional dyeing”
Content =“Buddha” and C_Object =“Face”
THEN (Base_Color,Dyeing_Color)=(RGB(136,108,96), RGB(250,126,68))

R3: IF Dynasty =“SUI dynasty” and Style =“Chinese white face” and
Content =“Buddha” and C_Object =“Face”
THEN (Base_Color,Dyeing_Color)= (RGB(255,255,255),None)

R4: IF Dynasty =“SUI dynasty” and Style =“TIAN-ZHU genetic method” and
Content =“Buddha” and C_Object =“Face”
THEN (Base_Color,Dyeing_Color)= (RGB(190,155,137),RGB(252,128,66))

3.3 Hybrid Reasoning Strategy

Our integrated system models the problem domain using the concepts of Classes along with Rules. This is a framework that gathers all known information about an object. The known information may be lists of possible values, initial values, default values, or inherited values for some colors. More importantly, such a framework not only provides values for the objects, but also ways of obtaining the values.

According to the four types of knowledge, we create four subclasses, which are the cave environment class (CEnvironment), the color distribution class (CDistribution), the painting style class (PStyle), and the color template class (CTemplate). For the common attributes and operations in the four classes, a frame base class (BFrame) is created. The frame-based reasoning is the main mechanism in the process of determining colors. It is achieved by comparing the descriptions of incoming facts with the frames in the knowledge base and retrieving the class frame that best matches the situation. If a given slot has no value or no slot has a value, the control is transformed into rule-based reasoning, database retrieval, or object class inheritance to obtain values. The main inference mechanism for applying general information to specific instances is inheritance. We use rule-based reasoning as the assistant mechanism to fire a sequence of rules by using incoming facts.

4 Image Processing Techniques

In order to restore mural colors, we first have to extract the image regions in which the pigments have discolored. The mural images are more difficult to process than the other type of images, not only because different pigments have partly decayed and have interpenetrated in varying degrees, but also because different pigments have different chemical compositions and different murals in different ages have different environmental conditions. As a result, one color may come from several pigments and one pigment may also change into several colors. All these factors make the murals' color changes very complex. In order to tackle this difficult problem, we have studied and utilized several image processing approaches which are detailed as follows.

4.1 Visual Color Space

The human perception of color is a complex physiological phenomenon. Up to now, human beings have not yet fully understood its mechanism and many conclusions relative to colors have been obtained by experiments. Consequently, various solid shape or color models, such as pyramid, cone, spheroid, as well as some irregular bodies, are used to describe colors. These models (also called color spaces) can be categorized into three classes: chromatic, industrial, and visual. The visual models use Hue, Saturation, and Luminance (or intensity) (HSL) to describe color information. They correspond more closely to the human perception of color.

4.2 The Oddity of the Visual Color Space

Since the hue component in the HSL color space integrates all chromatic information, it is more powerful and successful for the segmentation of color images than the primary colors, red, green, and blue, in the RGB color space. However, the HSL color space has a problem referred to as the oddity of the visual color space. Generally speaking, when 1) the values of RGB components of a pixel are proximal and 2) the saturation is too high ($s > 90\%$) or is too low ($s < 10\%$), the oddity will occur. In these cases, the hue of a pixel is undefined. A slight change of RGB component values can result in a large fluctuation of the hue value. This means that the hue value has a divergent distribution in its histogram from which it is difficult to identify the peak value to be used to segment the images as described in the next section.

Fig. 3 shows two color distributions in RGB and HSL spaces calculated from two typical colors from Dunhuang murals. Fig. 3a shows the histograms of a gray color whose RGB components have peak values of 70, 82, and 82, respectively. Its hue component value ranges from 109 to 203 and shows obvious divergent distribution. In this case, using HSL color space to segment images cannot obtain satisfactory results. Fig. 3b shows the histograms of a tangerine color whose RGB components have peak values of 178, 147, and 106, respectively. Its hue distribution is regular. The general strategy to deal with the oddity of the visual color space is the avoidance method [5]. We thus propose that the pixels with oddity in the visual space are processed in RGB space, while other pixels are still processed in HSL space.

4.3 Region Growing in Multiple Color Spaces

Many methods [6], [7] have been proposed for color image segmentation. Unfortunately, no single method is applicable to all types of images. Considering the fact that only partial contents in an image are required to be processed, we take some special measures to improve traditional methods.

We adopt a region growing and merging approach to extract the interesting color regions or color objects. If a pixel's color satisfies one of the following criteria (expansion criterion, region criterion, and seed criterion), it belongs to the region under analysis:

$$\begin{cases} d_{g1}(C(i,j), C(m,n)) \le \delta_{ptp} \\ d_{g2}(C(i,j), \overline{C_R(i,j)}) \le \delta_{ptr} \\ d_{g3}(C(i,j), C_s(i,j)) \le \delta_{pts}, \end{cases}$$

where $C(i,j)$ denotes the color of the checked pixel (i,j), $C(m,n)$ the color of the expansion pixel (m,n), $\overline{C_R(i,j)}$ the average color of the growing region, and $C_s(i,j)$ the color of the seed pixel. δ_{ptp}, δ_{ptr}, and δ_{pts} denote the threshold values of these criteria. Their sizes should satisfy $\delta_{pts} > \delta_{ptr} > \delta_{ptp}$. The process of region growing is described as:

Step 1: Push the seed pixel and its 3×3 adjacent pixels into a stack: stack[ps++]=seed+i. Mark down the region number in a label image: Lab_image[nx*img_height+ny]=N_region;

Step 2: Take an expansive point out of the stack

Step 3: Calculate the distances between checked pixel and seed pixel, expansive pixel, as well as growing region in RGB and HSL color spaces:

D1_rbg (seed(R, G, B), (r, g, b)); D1_hsl (seed(H, S, L), (h, s, l));
D2_rbg (neighbor(R, G, B), (r, g, b)); D2_hsl (neighbor(H, S, L), (h, s, l));
D3_rbg (mean(R, G, B), (r, g, b)); D3_hsl (mean(H, S,L), (h, s, l));

Step 4: If saturation $s < 10\%$ or the differences of RGB components are small, then

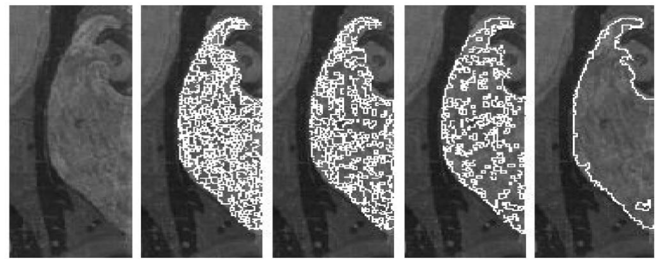
FF=D1_rbg<16 | | D2_rbg<8 | | D2_rbg<10;
else FF=D1_hsl<20.0 | | D2_hsl<4.0 | | D3_hsl<16.0;

Step 5: If FF is true and Lab_image[nx*img_height+ny]=0, push the point into the stack; Mark down the region number in label image: Lab_image[nx*img_height+ny]=N_region; Calculate the average color of the region: mean(H,S,L) and mean(R,G,B);

Step 6: If the stack is not empty, go to Step 2; else end the growing process;

Color distance determines the segmented region characteristics and the segmentation results. We adopt Minkowski color distance measurement. It is expressed as:

$$d(Minkowski) = \left(\sum_{k=1}^{p} \left| (C_i^k - C_j^k) \right|^p \right)^{\frac{1}{p}}.$$



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

Fig. 4. Image segmentation based on region growing and region merging.

In the HSL color space, the hue, saturation, and luminance component plays different roles for the human perception of color. For the simulation of this in segmenting images, we allow each component in the HSL color space to have its own parameter p. Thus, the distance can be expressed as:

$$d_M(i,j) = (|H_i - H_j|^a + |S_i - S_j|^b + |I_i - I_j|^c)^{\frac{1}{d}},$$

where parameters a, b, and c satisfy the inequality: $a > b > c > 0$ representing the decreasing importance of hue, saturation, and luminance to the human perception of color. In the experiments described below, we let $a = 3$, $b = 2$, $c = 1$, and $d = 1/2$. When using RGB color space, Euclidean distance is used instead.

4.4 Region Merging

The results produced by the region growing procedure described above usually contain a lot of fragmented regions. To solve this problem, we propose a region merging technique to combine these fragmented regions into bigger connected ones.

Besides the color information, the size of the fragmented region is an important factor to be considered when merging them. If the kernel size is too big, some of fragmented regions that should be connected may be left out. If the kernel size is too small, it may be impossible to merge the fragmented regions. The experiments show the size of 5×5 pixels is a good value suitable for the processing of Duanhuang mural images at hand. The algorithm for region merging is described as:

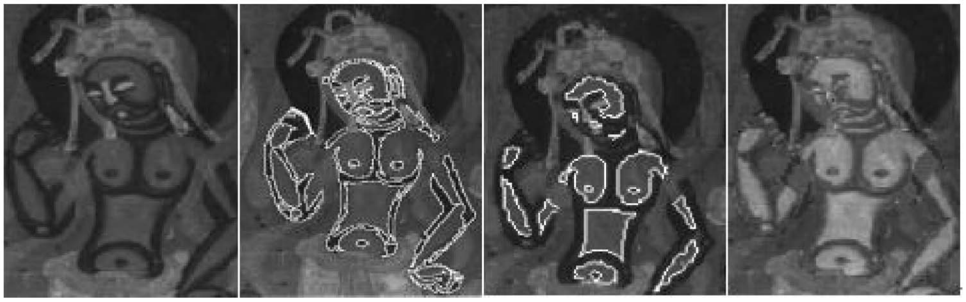
Step 1: Determine the circumscribed rectangle of the region N_region: rect_region(N_region,left,right,bottom,top)

Step 2: Extract the fragmentary regions in the rectangle:

```
for(x=left; x<=right; x++)
  for(y=bottom; y<=top; y++)
    if Lab_image[x*hight+y] !=0, take the next point
       mark down the region number in label image {
      push the point into stack: push_stack(x,y);
          do{ take point out of stack: pop_stack(cx,cy)
               if its adjacent point satisfies
                Lab_image[(cx+i)*hight+cy+j]=0,
               push it into stack: push_stack(cx+i,cy+j) and
                calculate the region size
          }while (size of the fragmentary region
                     is larger than 5 or stack is empty)
      }
```

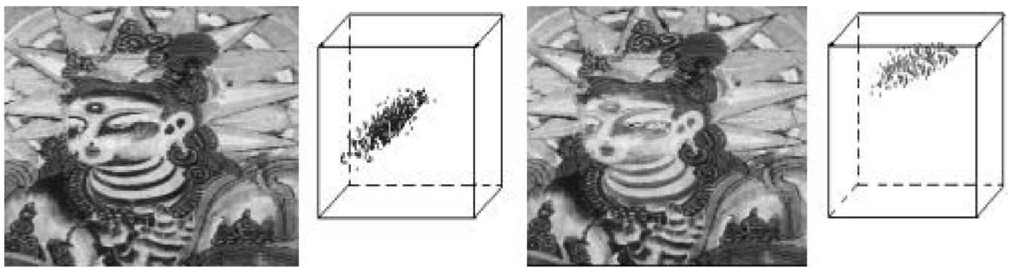
Step 3: If the fragmentary region is extracted, then calculate its mean color μ_i

Step 4: If $|\mu_r - \mu_i| < \delta_R$, this fragmentary region in label image are marked as N_region;



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

Fig. 5. The restoration of skin color of a bodhisattva.



(a) (b)

Fig. 6. The restoration of facial faint dyeing of a bodhisattva.

Fig. 4 shows an example of segmentation of a Dunhuang image. Fig. 4a shows the original image. Although the image has a blue hue as a whole, its color density is not uniformly distributed. Fig. 4b shows the segmentation result where only the seed criterion is considered. Fig. 4c shows the segmentation result where both the seed and the region criteria are considered. Fig. 4d shows the segmentation result where all three criteria described above are considered simultaneously. From these figures, we can see that each figure reveals a better performance of the algorithm than its previous ones. However, there exist many fragmented regions after region growing. Fig. 4e shows the result after region merging. A size of 5×5 pixels is chosen to merge fragmented regions in this case. After the region growing and merging process, only some relatively big regions are left.

It is unnecessary to use a constant to describe the size of the fragmented region. In practice, a trade off has to be made between the regions to be merged and retained when deciding the size of the kernel for such a process. However, the merging threshold value of δ_R should be bigger than the thresholds used in the region growing process.

5 Color Restoration

After color regions (or color objects) have been extracted using the method as described in Section 4 from the input image, their corresponding color histograms can be generated in HSL color space and their corresponding color distributions can be determined. Their restored colors can be obtained by the hybrid frame and rule-based reasoning approach. The attribute values, such as dynasty, age, cave, mural topic, content, painting style, etc., used for reasoning are interactively specified by the user through the dialog box. The restored colors are estimated using the following transformations:

$$H_{oi'} = H_{oi} + (H_{ohis} - H_{rmean}) \times D_h$$

$$S_{oi'} = \begin{cases} \frac{(S_{oi}-S_{o\min})\times(S_{r\max}-S_{r\min})}{S_{o\max}-S_{o\min}} + S_{r\min}, & \textit{if color template is used.} \\ S_{oi} \times \frac{S_{rmean}}{S_{ohis}} \times D_s, & \textit{if rule base is used.} \end{cases}$$

$$L'_{oi} = \begin{cases} \frac{(L_{oi}-L_{o\min})\times(L_{r\max}-L_{r\min})}{L_{o\max}-L_{o\min}} + L_{r\min}, & \textit{if color template is used.} \\ L_{oi} \times \frac{L_{rmean}}{L_{ohis]}} \times D_l, & \textit{if rule base is used.} \end{cases}$$

where $(H_{oi'}, S_{oi'}, L_{oi'})$ are the restored colors, (H_{oi}, S_{oi}, L_{oi}), $(H_{o\min}, S_{o\min}, L_{o\min})$, and $(H_{o\max}, S_{o\max}, L_{o\max})$ are the original, minimum, and maximum colors of an extracted discolored region, respectively, $(H_{ohis}, S_{ohis}, L_{ohis})$ are the peak values of the color histograms of an extracted discolored region, $(S_{r\min}, L_{r\min})$ and $(S_{r\max}, L_{r\max})$ are the minimum and maximum values obtained from the color template, $(H_{rmean}, S_{rmean}, L_{rmean})$ are the color values obtained from the rule base, and $(D_h, D_s, D_l) \in (0..1]$ are the constants.

Fig. 5 shows the color restoration results of a bodhisattva's skin. Fig. 5a shows the image with changed colors. The bodhisattva's skin colors have become black and gray owing to the color change of the red lead. Fig. 5b and Fig. 5c show the segmented images using the segmentation algorithm as described in Section 4. Fig. 5d shows the color restoration result. Based on the mural's cave, dynasty, age, content, topic, and other attributes, the inference engine reasons out its original colors as brown red and flesh red.

Fig. 6 shows another example of color restoration. Fig. 6a shows a faded fresco and the color distribution in the bodhisattva's facial faint dyeing and Fig. 6b shows the restored image and the color distribution in the bodhisattva's facial faint dyeing.

From these experiments, we can see that the restored colors of ancient murals are vivid, harmonic, and believable. In the wall paintings of Dunhuang, red lead pigment was extensively used on the face and body of the painted figures and most of them have, to date, become dark. So, the color restoration of red lead has a representative significance.

6 Conclusion

We described in this paper a computer-aided system to facilitate Dunhuang mural preservation research. The system can be used to aid artificial mural imitating, check pigment color fading rules under various environments, and simulate virtual changing processes of murals' colors over different ages. Experiments based on real images have shown that our proposed approach is effective and practical in restoring the original colors of ancient murals. We believe that the system is an important and necessary prerequisite for the future preservation and restoration of these unique frescoes in the history of human beings. Our future work will contain two aspects: 1) improving image segmentation techniques in order to separate different spoiled parts of murals more accurately and automatically and 2) collecting more knowledge about mural pigments and color changing rules.

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