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Xiaofeng Ye · Jinhui Yu · Qunsheng Peng

Virtual repair of ancient Chinese bronze articles

Abstract We present a novel method for repairing ancient Chinese bronze articles in digitized photographs, aiming at removing corrosion stains and restoring broken portions of the bronze articles. The key idea of our approach is to separate color from textures during the repairing process. We utilize Perlin noise to approximate the roughness of the bronze surface and fill-in the detected portions on the bronze articles in the input image, the chromatic content is added to Perlin noise with the hue and saturation components estimated by populating the grid over the detected portions with seed values taken from the exterior and interpolating in between to get values at non-integer points. The lighting effect on the detected portions is preserved by estimating the value component with a simple weighted sum. Our method repairs images of bronze articles fairly fast and the repaired images look plausible, as demonstrated for a variety of input images that exhibit different kind of defects including corrosion stains and broken portions on bronze articles.

Keywords · filling-in · in-painting · image repair · bronze articles

Xiaofeng Ye
1. State Key Lab. of CAD&CG, Zhejiang University, China
Tel.: +86-571-88206681
Fax: +86-571-88206680
E-mail: yexiaofeng@cad.zju.edu.cn
2. School of Computer and Engineering, WenZhou University, China

Jinhui Yu
State Key Lab. of CAD&CG, Zhejiang University,China
Tel. and Fax: the same as above
E-mail: jhyu@cad.zju.edu.cn

Qunsheng Peng
State Key Lab. of CAD&CG, Zhejiang University, China
Tel. and Fax: the same as above
E-mail: peng@cad.zju.edu.cn

1 Introduction

Bronze is an alloy of copper, tin and a small amount of lead. Its appearance marked the advancement of human culture from the Stone Age to the Bronze Age. From the 17th century BC to the Han Dynasty (206BC-AD200), Chinese people used rare and precious bronze to cast large quantities of ritual vessels, musical instruments and weapons that were elegant in form, finely decorated and clearly inscribed with various patterns. They affirm the artistic achievements of ancient China, and demonstrate how early Chinese used their ingenuity to create works that incorporated both science and art from natural resources.

Over the millennia, bronze articles exposed to high humidity or buried underground underwent the development of the cyclic corrosion phenomenon known as bronze disease, resulting in corrosion stains on the bronze surface. Some bronze articles may even break for unknown reasons. Physical and chemical based repairs will have an adverse effect on the appearance of the bronze antique, will seriously diminish its authenticity, and will significantly reduce its value as a source of historical information. It would be therefore desirable to virtually repair the ancient bronze so that we can better appreciate their original appearance without physical and chemical operations on the bronze antique.

Most of ancient Chinese bronze imageries available in public are photographs taken either in the museum or in the laboratory after the bronze articles were excavated, our goal is to virtually repair bronze articles in these photographic images, such as removing corrosion stains from the bronze surface, or filling-in the broken portions with the missing data in a visually plausible way.

In this paper we present a new method to repair corroded or broken portions on the bronze articles in the digitized photographs. The most relevant work to this study is in-painting and texture synthesis. The goal of in-painting is to restore the missed or damaged portions of the photos in a way not detectable by the viewer, the

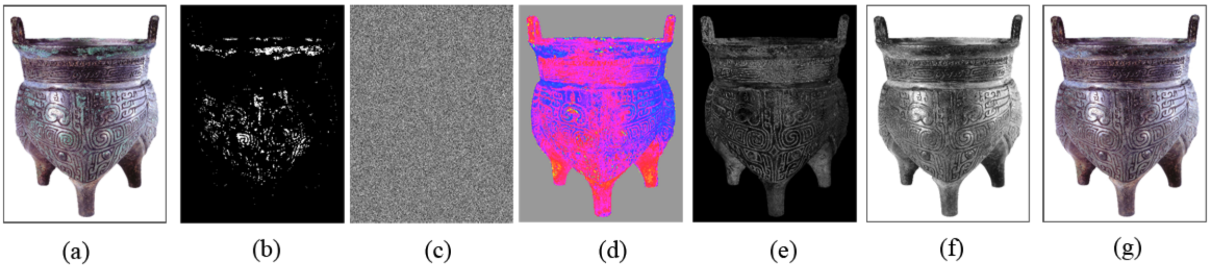

Fig. 1 Overview: (a) Input image, (b) mask of repaired portions (corrosion stains), (c) Perlin noise (d) estimated hue (H) component, (e) estimated saturation (S) component, (f) estimated value (V) component, (g) final result after filling in repaired portions with estimated H, S and V components.

in-painting is also known as image completion in literature.

Bertalmio et al [3] introduce image in-painting that fills in holes in an image by propagating image Laplacians in the isophote direction continuously from the exterior. Ballester et al [1] formulate the in-painting problem in a variational framework. The Euler' elastic is incorporated as a prior by Chan and Shen [6] to handle curve structures. Levin et al [19] perform image in-painting in the gradient domain using an image-specified prior. Recently some methods [23,8,9,25,26,17] operate by extending adjacent textures and contours into the unknown region.

Example-based approaches [16,14,5,2] have also been proposed for image completion by synthesizing pixels using texture synthesis techniques [10,11,18,20]. Chong combines weighting of the highest priority in [14] and the closest approximation by distance measure in [16] to repair damaged digital pictures [7]. Hays and Efros [15] perform the image completion powered by a huge database of photographs.

Some of in-painting techniques work well for small gaps, thin structures and text overlays. For large missing regions or textures regions, they may generate blurring artifacts. With some guidance, either automatically [4, 13] or interactively [21,9,24], some salient structures can be preserved in the filled regions. In the multi-resolution texture synthesis [27], the intensity gradient can be preserved in the synthesized texture image by summing synthesized low frequency and high frequency images.

Most of existing in-painting techniques directly utilize the information of colored textures from the exterior of detected portions and produce some nice results. Generally, fast in-painting algorithms may result in blurring artifacts, and good in-painting quality usually requires longer time in execution.

This study proposes a new in-painting strategy especially suitable for removing corrosion stains and repairing broken portions of bronze article in photographs with obvious lighting effects. The key idea of our method is to separate color from textures during the repairing process, we avoid blurring artifacts and slow texture search associated with most of existing in-painting techniques. An overview of our approach is described next.

2 Overview

Given an image I of the bronze article with the surface region Φ, on which there is a corroded region set Ω and un-corroded region set $\Phi - \Omega$, usually Ω contains multiple portions corresponding to corrosion stains or broken portions. In the rest of the paper we simply use Ω to indicate portions need to be repaired.

We first convert I from RGB to HSV space, and then detect Ω in Φ to make a binary mask, the mask is of the equal size as the input image I, we use Perlin noise to approximate the roughness of the bronze surface in Ω, the H and S components in Ω are estimated by interpolating seeds taken from surrounding parts of Ω in $\Phi - \Omega$ and populated on the grid over Ω, the V component is estimated by a simple weighted sum and the final repaired bronze image is obtained by filling-in Ω with the estimated H, S and V components. Fig. 1 shows the process of our repair method.

In the next 4 sections we proceed to describe each step involved in our repairing theme in detail.

3 Identification of corrosion stains and broken portions

Due to the complex mechanism for the production of corrosion stains on the bronze surface, such as different amount of copper, tin and lead in the alloy, various conditions that bronze articles underwent, corrosion stains usually distribute in a random manner on the bronze surface, with varying shape and size. Automatic identification of these corrosion stains is extremely hard, and manual marking those corrosion stains is also tedious, we therefore seek for semi-automatic identification methods.

In our system we provide a set of tools to identify corrosion satins by use of H or V component. Take the bronze article shown in Fig. 1(a) for instance, we first convert the input image from RGB to HSV space, and

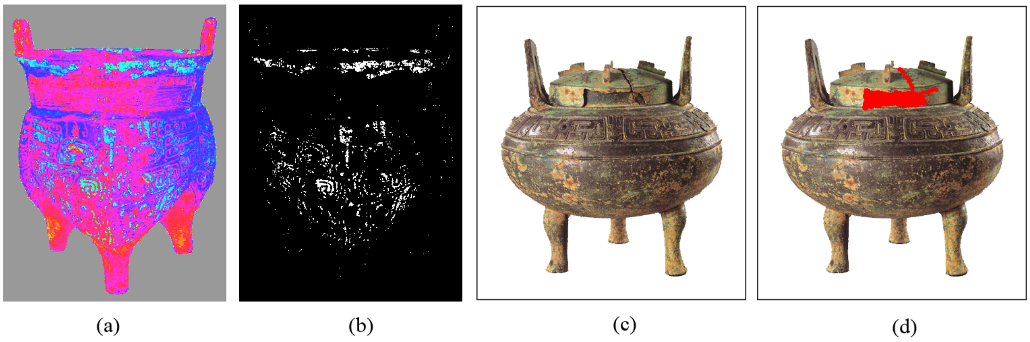

Fig. 2 Identification of repairing portions: (a) the hue component, (b) identified portions in white, (c) broken bronze article, (d) manually marked broken portion in red.

the image of H component is displayed (Fig. 2(a)), in this example the H component corresponding to corrosion stains appears somewhat light blue, our UI allows users to click a point in the light blue portions to pick up a seed H value hs and then set a tolerance ht, our system next searches for the H values falling in the range $[hs - ht, hs + ht]$ and those pixels with above H values are identified as corrosion stains in Ω. The instant visual feedback is given so that users can vary ht to get desired result.

In addition to the identification of corrosion stains with H component, users can alternatively identify corrosion stains by use of V component in a similar manner.

In the case of that corrosion stains cannot be identified through the H and V component in a satisfactory way, we let users manually specify the corrosion stains instead, as most of existing filling-in systems do.

In most cases, broken portions are bigger in size compared with corrosion stains, and their shapes are also irregular, as shown by an example in Fig. 2 (c). Using the interactive tool provided in our system users can mark broken portions manually, as indiacted with red color in Fig. 2 (d).

4 Modeling the roughness of the bronze surface

In ancient China, two main methods were used to cast bronze articles, the clay mould method and the lost-wax method. The clay mould method included the procedures of making outer moulds, making inner moulds, drying the moulds, combining the moulds, smelting and casting. The lost-wax method included the procedures of making inner moulds, applying wax and carving, making outer moulds, melting wax and drying the moulds, smelting and casting. In both methods the clay moulds were finally used to cast bronze articles, as a result the surface of bronze articles had microstructures due to the roughness of the clay moulds, these microstructures appear as textures on the bronze surface in photographs. In Fig. 3 (a) we show a patch of enlarged bronze surface textures taken from un-corroded area on the surface of bronze articles.

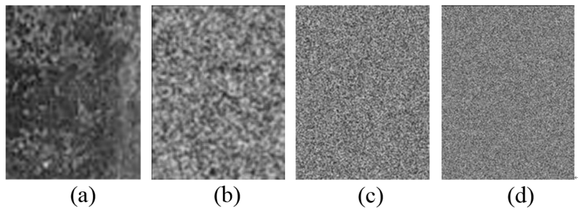

Fig. 3 Perlin noise with different scales: (a) enlarged bronze surface textures, (b) original Pelrin noise with grid size=2 pixels, (c) scaled down to 1/3, (d) scaled down to 1/5.

Visually textures shown in Fig. 3 (a) resemble very much to Perlin noise [22], we therefore adopt the Perlin noise to approximate the bronze surface texture in photographs. The algorithm of generating the Perlin noise over the given area on 2D involves populating the grid with random values and interpolating in between to get values at non-integer points. For implementation detail of Perlin noise please refer to [22].

Physical bronze articles vary dramatically in size because they were made for different purposes, while in photographs scanned from books bronze articles are usually moderate-sized for a better view, thus textures on the bronze surface in photographs may appear with varying degree of roughness. To cope with those texture variations, we provide Perlin noise textures with 5 scales that are adequate for our repair task at hand. The original (roughest) one is Pelrin noise with grid size equal to 2 pixels. (Fig. 3(b)), and smoother ones can be obtained by scaling it by the following 5 factors 1/2,1/3 (Fig. 3(c)),1/4 and 1/5 (Fig. 3(d)). All above Perlin noise textures are pre-generated for the user to choose according to the required roughness for the repairing task.

5 Estimation of hue and saturation components

The Perlin noise generated is a gray value image which, if filled-in Ω straightforwardly, would look inconsistent

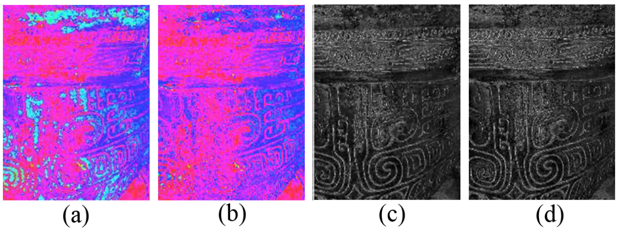

Fig. 4 Estimation of hue and saturation component: (a) original hue component, (b) estimated hue component, (c) original saturation component, (d) estimated saturation component.

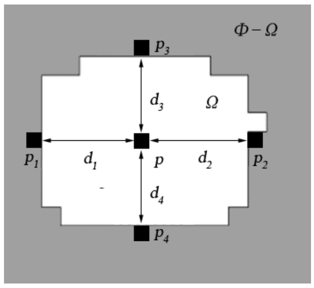

Fig. 5 Initial estimation of lighting by a weighted sum

in color from their surrounding parts of Ω in Φ-Ω. We need therefore to add the chromatic content to Perlin noise in Ω in order to ensure color consistency between Ω and its surrounding parts in Φ-Ω.

Fig. 4 (a) shows the H component of the first bronze article (local) in Fig. 1(a), where the light blue regions corresponds to corrosion stains Ω, while the purple, red and dark blue area correspond to un-corroded regions in Φ-Ω. Careful observation of Fig. 4(a) reveals that apart from changes of the H component caused by bronze patterns, the H component varies in a random manner in Φ-Ω. We estimate the H component in Ω by utilizing the H information in the surrounding parts of Ω in Φ-Ω, as detailed next.

After Ω is identified, we first calculate the bounding box for Ω and then lay a grid with size set to empirically to 2 pixels over the bounding box. Next we select seed H values for the integer points on the grid. In our system two options for obtaining the seed H values are offered: (1) sample the H values along the boundary of Ω in Φ-Ω and put them into ψ, or (2) select a patch manually in Φ-Ω, then sample the H values on the patch and put them into ψ.

The seed H values are taken randomly from ψ and populated over the grid, values at non-integer points over the grid can be obtained by interpolating in between. Let *startHue* (default 0) and *endHue* (default 359) denote the two seed hue values, respectively, the hue is interpolated in the range [*startHue*, *endHue*] when *sratHue*<*endHue*. Note that the H is periodic, thus a H of 360 degrees corresponds with a H of zero degrees. If *endHue*<*startHue* then the range [*endHue*, 359] and [0, *startHue*] is selected (thus anti-clockwise).

Fig. 4(b) shows the H image obtained by filling-in Ω with the estimated H component and the resultant H image looks plausible.

The S component in Ω is estimated in a similar manner. Note that the seed S values must be taken correspondingly from the same pixels where the seed H values are taken, to ensure the correct synthesis of the final colors using the estimated H and S components. Fig. 4(c) and (d) show the original S image and the estimated S component in Ω, respectively.

6 Estimation of the value component

The estimated H and S components only contribute to the color in Ω. In order to preserve the lighting effects in bronze photographs, we need to estimate the V component in Ω such that both lighting effects and textures in Perlin noise look plausibly consistent with surrounding parts of Ω in Φ-Ω.

Accurate estimation of lighting requires determination of bronze surface normal and direction of the light source. In most of Chinese bronze articles various decorative relief patterns are made on the bronze surface, thus the orientation of the surface normal on the relief patterns varies in a quite complex way. It is extremely hard to correctly reconstruct the 3D geometry for relief patterns on the bronze surface from photographic images.

Since the height of the relief patterns is quite small compared with the size of bronze articles, it is reasonable for us to approximate the bronze surface by the underlying smooth surface (i.e, the surface without relief patterns laid on) and estimate the lighting effect on such underling surface.

We first estimate the luminance value at a pixel p in Ω by a weighted sum of the luminance value of pixels along four directions on the boundary of Ω in Φ-Ω:

$$l(p) = 0.5(\frac{d_2 l(p_1) + d_1 l(p_2)}{d_1 + d_2} + \frac{d_4 l(p_3) + d_3 l(p_4)}{d_3 + d_4}) \quad (1)$$

where $l(p)$ is the luminance value at p, p_1 and p_2 are pixels on the left and right of p on the boundary of Ω, p_3 and p_4 are pixels on the up and down of p on the boundary of Ω, and d_i is the L^2 distance between p and p_i, (i=1,...4), as illustrated in Fig. 5.

The initial estimated lighting is shown in Fig. 6(a), due to our summation theme defined by equation (1), some artifacts like fabric patterns appear in Ω (right of Fig.6 (a)). We filter the initial estimated lighting image with artifacts using a Gaussian kernel with σ empirically set to 3 to obtain an improved lighting estimation (Fig. 6(b)) in which the fabric artifacts disappear.

The final estimated lighting image is then blended with Perlin noise to estimate V component in Ω:

$$V(p) = k_1 * EL(p) + k_2 * (PT(p) - M) \quad (2)$$

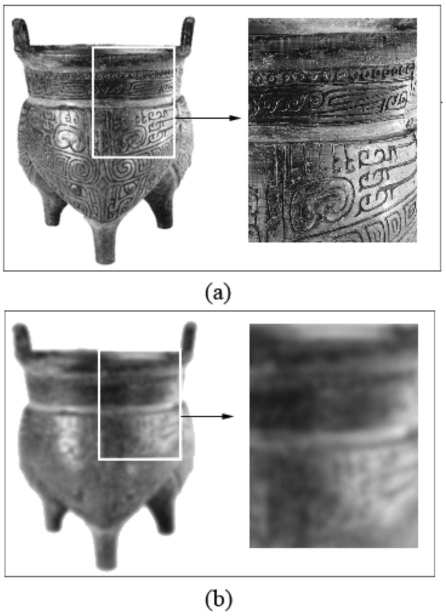

Fig. 6 Estimated lighting effect: (a) initial estimation by the weighted sum, (b) filtered result.

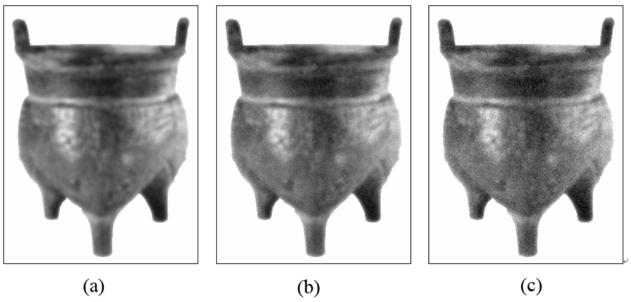

Fig. 7 Estimated V component with different weights: (a) k1=0.9, k2=0.1, (b) k1=0.7, k2=0.3, (c) k1=0.5, k2=0.5.

where $V(p)$ is the estimated V component at p, $EL(p)$ is the initial estimated lighting value at p, $PT(p)$ is the gray value of Perlin noise taken at p, M is the mean of Perlin noise, k_1 and k_2 are weights. A big k_1 would result in a brighter color in Ω, and a big k_2 would enhance the Perlin noise texture Ω. Fig. 7 shows the resulting V images with different k_1 and k_2. In our implementation we chose $k_1 = 0.7$ and $k_2 = 0.3$ as default values, users may tune them though our UI to get desired effect.

The estimated V component obtained with equation (2) usually has different mean and variances compared with those in the estimated lighting obtained with equation (1), we shift and scale the pixel data in the estimated V component such that its means and variations are precisely the same as the mean and variance of estimated lighting.

7 Results

Here we apply our algorithm to a variety of images, including bronze articles with corrosion stains and broken portions. All experiments were run on a ThinkPad X61(IBM X61) with 1024 M of RAM. The image size is bounded within 500x500 pixels, that is, if the height of the input image is bigger than its width, we confine its height to 500 pixels and its width is scaled proportionally.

The time to repair an image depends on heavily on the percentage of the masked pixels. In our experiments, masked pixels cover 4-15 % of the input image, and our algorithm took about 5-15 seconds for these masks.

7.1 Removal of corrosion stains

Fig. 8 shows enlarged image of Fig. 1(a) and three repaired images by Stay's method [23] (Fig. 8(b)), Chong's method [7] (Fig. 8(c)) and our method (Fig. 8 (d)). Stay's method took only 9 seconds to repair the image, the resultant image however has blurring artifacts. Result obtained by Chong's method is visually compatible to ours, the time spent on repairing process by the two methods however differs dramatically: 3 minutes and 4 seconds in Chong's method and 8 seconds with our approach.

7.2 Repairing broken portions

The second example is to repair broken portions on the bronze article. In this example we adopt two step operations: the broken portion on the bronze lid is repaired first, the resultant image is then used as the source image for corrosion stains removal. We present repaired results by Chong's and our method for comparison. The time spend on the two step repairing process are 1 minute 8 seconds and 5 seconds in total with Chong's and our method, respectively. In addition to the fast repair, our method also achieved better result than the Chong's method in the repaired image, there are much less yellow corrosion stains left on the bronze surface, as shown by (c) and (d) in Fig. 9.

7.3 Repairing portions with relief patterns

The third example is to repair broken portion with relief patterns on the bronze article (Fig. 10 (a)). In this case the broken portion is divided into two parts: smooth part without relief patterns and the part with relief patterns. To complete the repairing task, we have to fill-in the both parts with the corresponding missing data. In the exemplar-based in-painting [8], a best-first algorithm is proposed to propagate the confidence synthesized pixel values, and the texture structure can be maintained in

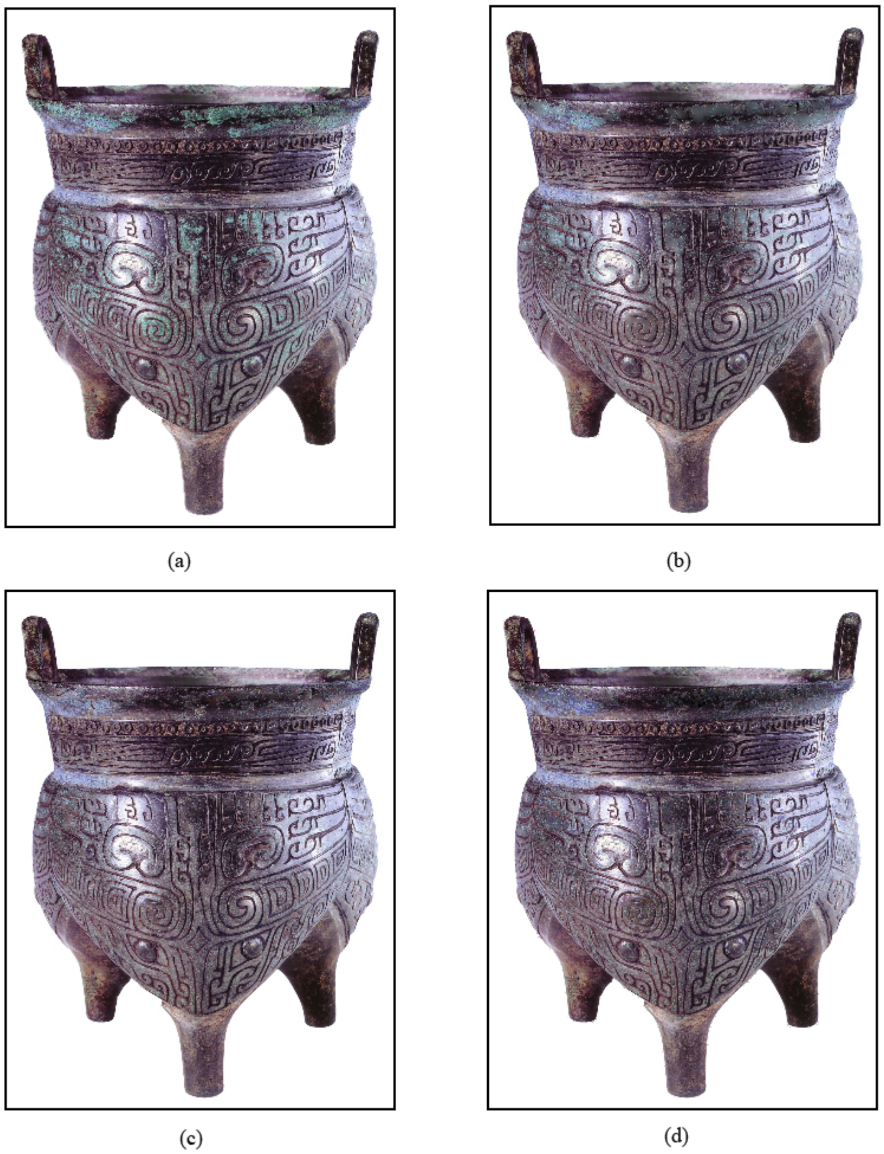

Fig. 8 Removal of corrosion stains: (a) Input image, (b) repaired image by Stay's method, (c) repaired result by Chong's method,(d) repaired image by our algorithm.

the filled region. Decorative patterns on bronze articles are however not uniformly textured as the case in [8], they have motifs with varying structures grouped in different ways, thus, in the region to be filled, the missing motifs can not be propagated with the structural information from their neighbor motifs.

Currently our method is also unable to directly reproduce pattern textures on the repaired portions, because the structural information of the pattern texture is not taken into account in our filling-in theme. In order to repair the broken portion with relief patterns, we first fill-in the broken portion with our algorithm to obtain an intermediate image (Fig. 10 (b), and then add the relief pattern textures interactively by blending the texture patch taken from the bronze surface with intermediate image in the broken portion. The final repaired image is shown in Fig. 10 (c) which looks plausible.

8 Conclusion and future work

This paper has presented a novel algorithm for removing corrosion stains and repairing broken portions in photographs of Chinese ancient bronze articles. The result of repair is an image in which the selected portions have

Fig. 9 Repairing broken portions: (a) input image, (b) result of first step by Chong's method , (d) result of second step by Chong's method (e) result of first step by our method (e) result of second step by our method.

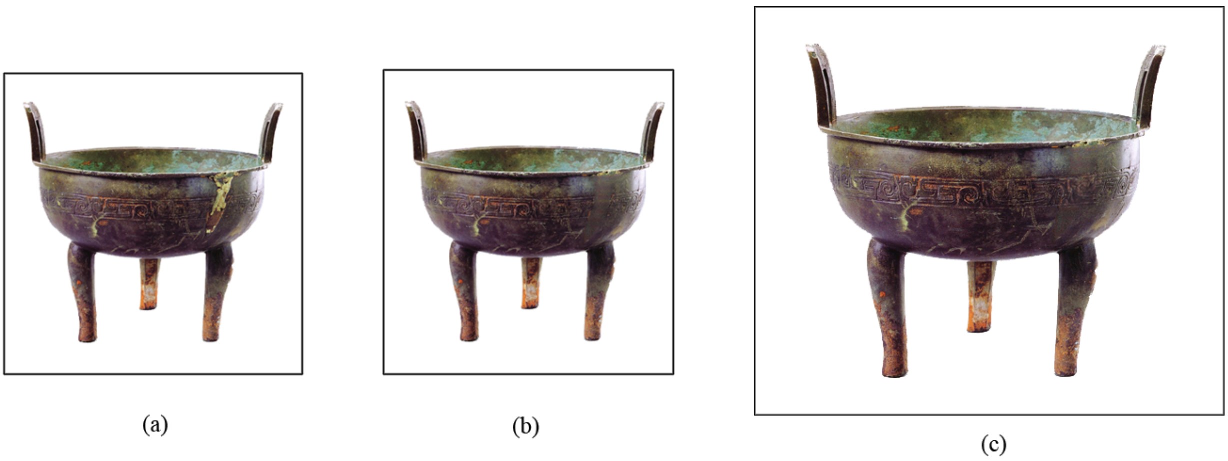

Fig. 10 Repairing broken portion containing relief patterns: (a) original image, (b) intermediate repaired image by our method, (c) final image by adding relief pattern textures.

been replaced by the estimated H, S and V components, using the information from surrounding parts of the repaired portions or the selected patch on un-corroded or un-broken area.

Our approach employs Perlin noise to approximate the roughness of the bronze surface, the use of Perlin noise avoids the blur artifacts and slow texture search associated with most of existing in-painting algorithms, and our V component estimation theme enables the lighting effect on the bronze articles to be preserved in a plausible manner. We believe the proposed technique is applicable not only to the repair of ancient bronze articles in photographs, but also to the repair of ancient paintings and murals, such as removing mold and mildew stains as well as crevices, as long as we replace Perlin noise with appropriate paper and wall textures in the system.

Repairing selected portions with structural relief patterns on bronze articles remains a challenging problem. This requires identification of different types of motifs as well as the spatial arrangements of those motifs in the relief patterns and is a topic for future work.

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References

1. Ballester B., Caselles V., Verdera J., Bertalmio M., and Sapiro G. A variational model for flling-in gray level and color images. In Proceedings of the 8th International Conference on Computer Vision, **Vol** 1, 10-16, Vancouver, Canada, (2001)
2. Barret, A., and Cheney, A. Object-based image editing. In Proceedings of ACM SIGGRAPH 2002, 777C784. (2002)
3. Bertalmio M, Sapiro G, Caselles V, et al. Image inpainting. In Proceedings of SIGGRAPH 2000. New Orleans, USA,417-424 (2000)
4. Bertalmio, M., Vese, L., Sapiro, G., and Osher, S. Simultaneous structure and texture image inpainting. In Proc. Conf. Comp. Vision Pattern Rec., II.707C714 (2003)
5. Bornard, R., Lecan, E., Laborelli, L., and Chenot, J.-H. Miss- ing data correction in still images and image sequences. In Proc. ACM Int. Conf. on Multimedia, 355C361 (2002)
6. ChanT, F., Kang, S.-H., and Shen, J., Eulers elastica and curvature based inpaintings, SIAM J. Appl. Math., **Vol** 63(2), 564C592 (2002)
7. Chong, H., Image Inpainting and Texture Synthesis, http://www.people.fas.harvard.edu/ hchong/ Spring2002/cs276r/
8. Criminisi, A., Perez, P., And Toyama, K. Object Removal By Exemplar-Based Inpainting. Cvpr **Vol** 02, 721 (2003)
9. Drori, I., Cohen-Or, D., And Yeshurun, H. Fragment-Based Image Completion. Acm Trans. Graph. **Vol** 22(3), 303-312 (2003)
10. Efros, A., and Leung, T. Texture synthesis by non-parametric sampling. In Proceedings of Inte. Conf. on Comp. Vision, 1033C1038 (1999)
11. Efros, A. A., And Freeman W. T. Image Quilting For Texture Synthesis And Transfer. In Proceedings of Siggraph, 341-346 (2001).
12. Harrison, P. A non-hierarchical procedure for re-synthesis of complex textures. In Proc. Int. Conf. Central Europe Comp. Graphics, Visua. and Comp. Vision. (2001)
13. Jia, J., and Tang, C. K. Image repairing: robust image syn- thesis by adaptive nd tensor voting. In Proc. Conf. Comp. Vision Pattern Rec., I643C650 (2003)
14. Harrison, P. A non-hierarchical procedure for re-synthesis of complex textures. In WSCG'2001, 190-197 (2001)
15. Hays, J., Efros, A.A., J. H., Efros, A.A., Scene Completion Using Millions of Photographs,In Proceedings of ACM SIGGRAPH 2007, (2007)
16. Igehy, H., and Pereira, L. Image replacement through texture synthesis. In Proc. of Inte. Conf. on Image Processing, 186C189 (1997)
17. Komodakis, N. Image Completion Using Global Optimization. In Cvpr, 442-452 (2006)
18. Kwatra, V., Schodl, A., Essa, I., Turk, G., And Bobick, A. Graphcut Textures: Image And Video Synthesis Using Graph Cuts. Acm Trans. Graph. **Vol** 22(3), 277-286 (2003)
19. Levin, A., Zomet, A., and Weiss, Y. Learning how to inpaint from global image statistics. In Proceedings of Inte. Conf. on Comp. Vision, II.305C313 (2003)
20. Kwatra, V., Essa, I., Bobick, A., And Kwatra, N. Texture Optimization For Example-Based Synthesis. In Acm Trans. Graph., 795-802 (2005)
21. Perez, P., Gangnet, M., and Blake, A. 2004. Patchworks: example- based region tiling for image editing. Technical Report, Microsoft Research, MSR-TR-2004-04. (2004)
22. Perlin, K. An image synthesizer. Computer Graphics, 19(3):287C296, July 1985.
23. Stay D.S.,Inpainting, http://iat.ubalt.edu/summers/math /inpainting.htm.
24. Sun, J., Yuan, L., Jia, J., And Shum, H-Y. Image Completion With Structure Propagation. Acm Trans. Graph. **Vol** 24(3), 861-868 (2005)
25. Wexler, Y., Shechtman, E., And Irani, M. Spacetime Video Completion. Cvpr **Vol** 01, 120-127 (2004)
26. Wilczkowiak, M., Brostow, G. J., Tordoff, B., And Cipolla, R. Hole Filling Through Photomontage. In Bmvc, 492-501 (2005)
27. Yamauchi H., Haber J. O.r, And Seidel H-P , Image Restoration Using Multiresolution Texture Synthesis And Image Inpainting, Proc. Computer Graphics International, 120-125, Tokyo, Japan (2003)