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Completion of images of historical artifacts based on salient shapes

Mang Xiao [a,*], Guangyao Li [a], Lei Peng [a,b], Yangjian Lv [a], Yuhang Mao [a]

[a] College of Electronics and Information Engineering, Tongji University, Shanghai, PR China
[b] School of Information Engineering, Tai'an College, Shandong, PR China

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ABSTRACT

Protecting images of historical artifacts is of great value and cultural significance. In this study, we present a method for completing images of complex historical artifacts by referring to objects with similar shapes in other images. Our approach includes two fundamental stages. First, we reconstruct the salient shape of the damaged object using shape point set registration and curve fitting. Second, based on a shape guide map and gradients, we generate a new energy to complete damaged images of historical artifacts in terms of their shape and semantics. We obtained promising results with multiple images of historical artifacts, thereby demonstrating the superior performance of our proposed method compared with existing approaches.

1. Introduction

Image completion techniques are used to solve the problem of filling target region (or "hole") in image. This is a difficult problem in computer vision because the completed image must be visually plausible in terms of its shape and texture. In particular, completing images of damaged historical artifacts remains a challenging problem.

Two main types of image completion techniques are available. The first classical method is based on a single image. In some studies, the hole have been filled with a diffusion-based method [1,2], which is known as "inpainting". However, this method produces blurring and the results obtained after the repair process may be locally discontinuous in large-scale damaged images. Therefore, the exemplar-based method [3] is used to fill large damaged regions. The methods described in [4] proceed in a greedy manner, whereas Wexler et al. [5] employed an optimization method with a well-defined objective function, which yielded more coherent results. However, this approach is computationally expensive, although the fast PatchMatch method [6] relieves this problem greatly. It is difficult to obtain the full structure of an image using patch translation; thus, some methods [7–9] employ photometric and geometric transformations to address this issue.

The second method fills the target region with more information based on the structure and texture in multiple images [10]. For example, Hays and Efros [11] completed the target regions in scenes using graph cuts with an image of a similar scene from a huge image database, where the method was based on image retrieval technology. Mobahi et al. [12] used a similar approach to fill target regions including a damaged foreground object. Tang et al. [13] used a boundary band map to reconstruct the structure of a damaged foreground object and to fill target regions according to a greedy strategy. However, the high level accuracy of object reconstructions and the consistent filling of target regions based on sample image are still challenging problems.

In the present study, we present an innovative method for completing the target regions in images of historical artifacts using samples of similar images. Our method identifies similar objects based on salient shapes, which can be expressed as their shapes. The shape of the damaged object can be reconstructed with the salient shape of the sample object using the point set registration technique [14], although there is a relatively large degree of deformation between the shapes. Furthermore, the texture of the sample object can be used to fill the target region by histogram specification, and using photometric and geometric transformation.

The three main contributions of this study are as follows. First, the salient shape of the damaged object is reconstructed precisely. Second, the damaged image is completed in a seamless and consistent manner. Third, a global optimization method is proposed for completing images of historical artifacts using sample images.

* Corresponding author. Tel.: +86 18818203139.
E-mail address: 510mangxiao@tongji.edu.cn (M. Xiao).

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2. Salient shape reconstruction

The salient shape reconstruction process comprises two main steps. First, known shapes are extracted from the segmented foreground objects in the damaged image and sample image. Next, the reconstructed global shape of the damaged foreground object is calculated using the non-rigid registration method based on the two known shapes.

2.1. Shape extraction

A salient shape comprises the core structure of the foreground object. The foreground objects are segmented with the Grab Cut method [15] and the results are shown in Fig. 1(b and e). The shape of the foreground object is then extracted by Canny edge detection [16] and the results are shown in Fig. 1(c and f).

2.2. Shape reconstruction

We use the point set registration method to reconstruct the global shape of the damaged object. First, we provide a brief introduction to non-rigid point set registration, which utilizes a robust estimator called the L2 minimizing estimate (L2E) criterion [14]. Non-rigid registration helps to determine the correct correspondence between two point sets, such as the shapes extracted from two objects.

The goal of correspondence is to estimate a transformation $f: y_i = f(x_i)$ and to fit the inliers. To obtain the L2E estimator for the model $f(x|\theta)$, we minimize the function to evaluate the parameter θ.

$$L_2E(\theta) = \int f(x|\theta)^2 dx - \frac{2}{n}\sum_{i=1}^{n} f(x|\theta) \tag{1}$$

We assume that noise on the inliers is Gaussian distribution with uniform standard deviation σ and zero mean. Then we get the following equation:

$$L_2E(f, \sigma^2) = \frac{1}{2^d(\pi\sigma)^{d/2}} - \frac{2}{n}\sum_{i=1}^{n}\phi(y_i - f(x_i|0, \sigma^2 I)) \tag{2}$$

where d is the dimension of the point, and the size of identity matrix I is $d \times d$. An inlier point correspondence (x_i, y_i) satisfies $y_i - f(x_i) \sim N(0, \sigma_2 I)$. We define a reproducing kernel Hilbert space H with a positive definite matrix valued kernel $\Gamma : \mathbb{R}^d \times \mathbb{R}^d \to \mathbb{R}^{d\times d}$. The optimal transformation f takes the form:

$$f(x_i) = \sum_{i=1}^{m} \Gamma(x, \tilde{x}_i)c_i \tag{3}$$

where c_i is a $d \times 1$ dimensional coefficient vector. The chosen point set $\{\tilde{x}_i\}_{i=1}^{m}$ are somewhat analogous to "control points".

$$L_2E(C, \sigma^2) = \frac{1}{2^d(\pi\sigma)^{d/2}} - \frac{2}{n}\sum_{i=1}^{n}\frac{1}{(2\pi\sigma)^{d/2}} e^{-\frac{\left\|y_i^T - U_{i,\cdot}C\right\|^2}{2\sigma^2}} + \lambda \ \ tr(C^T \Gamma C) \tag{4}$$

where kernel matrix $\Gamma \in \mathbb{R}^{m\times m}$ is named the Gram matrix with $\Gamma_{ij} = \Gamma(\tilde{x}_i, \tilde{x}_i) = e^{-\beta\left\|\tilde{x}_i - \tilde{x}_j\right\|^2}$, $U \in \mathbb{R}^{n\times m}$ with $U_{ij} = \Gamma(x_i, \tilde{x}_j) = e^{-\beta\left\|\tilde{x}_i - \tilde{x}_j\right\|^2}$, $U_{i,\cdot}$ is the ith row of the matrix U, $tr(\cdot)$ is the trace, and $C = (c_1, \ldots, c_m)^T$ denotes the coefficient matrix.

Shapes of the damaged foreground object and the sample foreground object are shown in Fig. 2(a). Fig. 2(b) demonstrates the result of the registration. The global shape of the damaged foreground object is reconstructed successfully shown in Fig. 2(c), revealing the reconstructed outline complete and semantic. We set $\beta = 0.8$ and $\lambda = 0.1$ in algorithm. The parameter σ^2 and C were initialized to 0.05 and 0, respectively.

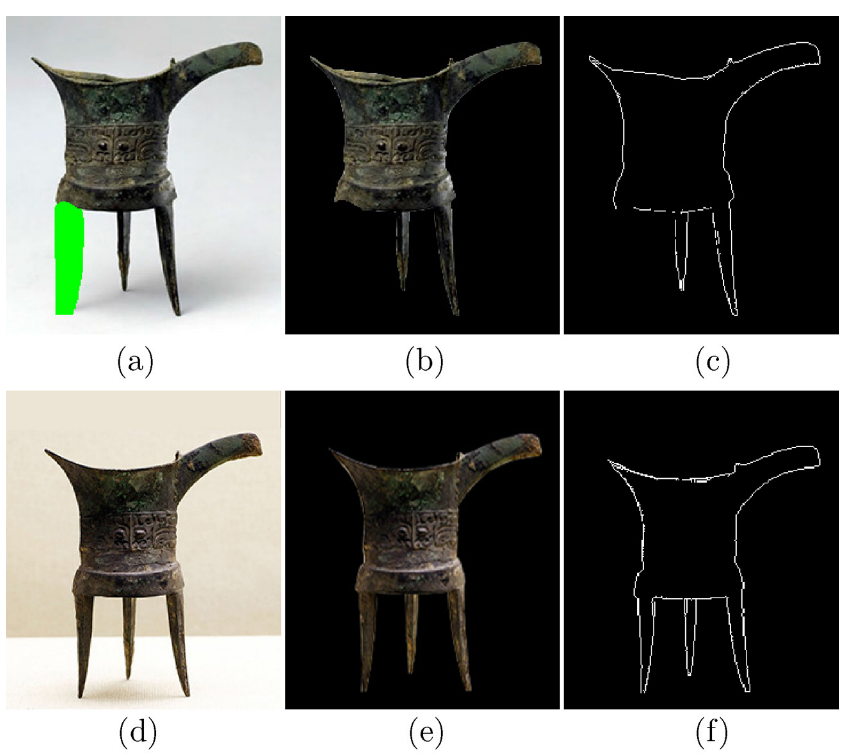

Fig. 1. Shape extraction. (a) Damaged image. (b) Damaged object. (c) Damaged object' s shape. (d) Sample image. (e) Sample object. (f) Sample object' s shape.