Layer-based Image Completion by Poisson Surface Reconstruction

Hengjin Liu[a,b], Huizhu Jia[b*], Xiaodong Xie[a,b], Xiangyu Kong[b], Yuanchao Bai[b], Wen Gao[a,b]

[a]*School of Electronic and Computer Engineering, Peking University Shenzhen Graduate School, Shenzhen, China*

[b]*National Engineering Laboratory of Video Technology, Peking University, Beijing, China*

{hjliu, hzjia, donxie, kong, yuanchao.bai, wgao}@pku.edu.cn

***Abstract*— Image completion has been widely used to repair damaged regions of a given digital image in a visually plausible way. However, it is difficult to infer appropriate information, meanwhile keep globally coherent just from the origin image when its critical parts are missing. To address this problem, we propose a novel layer-divided image completion scheme, which contains two major steps. First, we extract foregrounds of both target image and source image, and then we apply a guided Poisson surface reconstruction technique to complete the target foreground according to parameters obtained from optimal-matching calculation. Second, to fill the remaining damaged part, a related exemplar-based image completion algorithm is further devised. Several experiments and comparisons show the effectiveness and robustness of our proposed algorithm.**

***Index Terms*— Image completion, Layer-divided, Poisson equation, Priority map, Critical parts**

I. INTRODUCTION

Image completion is a very interesting and important topic in the field of computer vision and image processing. As a process of filling damaged or missing region of a digital image, image completion was firstly applied to fill nontextured or relatively narrow gaps in an image such as superimposed texts or scratches in 2000 [1]. In recent years, large-scale image information-damaged problem, especially object removal, brought out great interest [2]-[10].

Bertalmio et al. [1] firstly tried to fill the missing region by solving a partial difference equation (PDE). This PDE-based method and its variants merely work well when the missing regions are narrow and nontextured, otherwise it will produce blurs since only local information around the damaged region is used.

The second category is the examplar-based method. To avoid merely using local information, Criminisi et al. [2] tried to fill the missing region by copying the most similar patch from undamaged region, according to a guided priority map, which guarantee to propagate strong structures first. To avoid greedy patch assignment and ordering problem in [2], some approaches [3]-[4] posed image completion as a discrete global optimization problem. In these methods, the objective functions encode the energy of discrete Markov Random Field (MRF), and belief propagation (BP) and multiscale graph cuts were applied to optimize these energy functions to approach a global minimum, respectively. These methods also require enough similar patches, and work well for linear structures or random-texture content, however, they are very time-consuming.

Unfortunately, all these methods failed to complete images with critical parts of an object or foreground missing, for example, a bird with its head damaged, which do exist in the real world. In this context, the structure tendency in damaged region can hardly be inferred rationally except for linear structure, and usually there are not enough similar patches. To cope with this problem, several groups proposed other kind of solutions, which turn to user intervention [5] or source images [6]-[8] to acquire some necessary information, such as structure tendency, gradient map and so on.

Sun's method [5] requires users to draw curves to specify the structure tendency in damaged region. They divided the whole process into structure completion and texture completion. However, it's hard to draw precise curves for images with complicate structures. Hays et al. [6] proposed an amazing scene-matching completion method with the help of source images containing similar scene from the web, which is very memory- and time-consuming. Moreover, this method sacrifices too much original information of the target image. Perez et al. [7] reconstructed an object in target image seamlessly, which contain the same patterns as specified object in source image, by solving a Poisson equation with a guided gradient field. Although excellent results were achieved, this method assumes that the color of the source image is close to that of the target image. If not, the reconstructed color will distort heavily. Moreover, this method is suitable only for the whole object reconstruction without any parts losing.

Aiming to complete images with critical parts missing, and inspired by the idea of borrowing high-level information from source images like [6]-[8] and the "divide and rule" scheme like [5], we devise a foreground and background layer-divided scheme, in which the target image is divided into foreground and background layers, and this two layers are completed separately. Experiments and comparisons show that our algorithm can get more globally plausible results than the related state-of–the-art image completion methods.

The rest of this paper is organized as follows: in section II, we give the framework of layer-based image completion algorithm, and detail the foreground and background completion processes. Experiments and analysis are presented in section III. Finally, section IV summarizes this paper.

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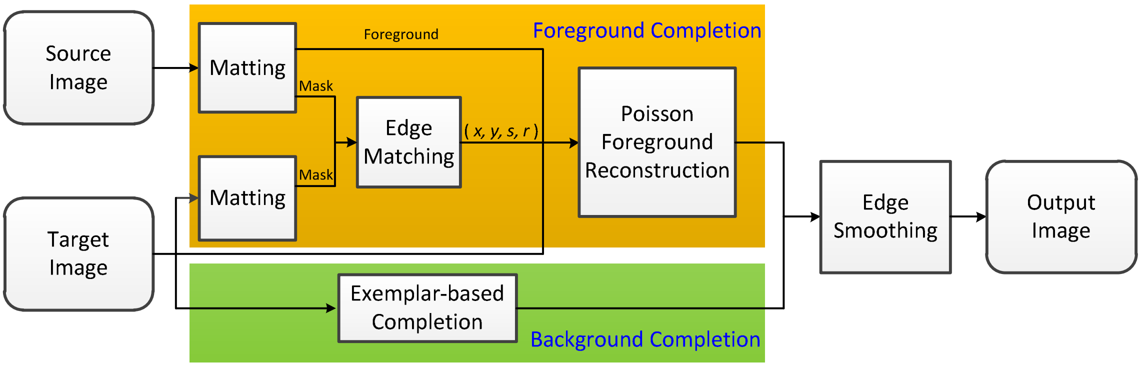

Fig. 1 Framework of layer-divided image completion algorithm.

II. The Proposed Method

Fig.1 shows the layer-divided scheme and illustrations of our proposed image completion algorithm. This algorithm contains two major phases: Poisson-based foreground completion and exemplar-based background completion.

In foreground completion phase, our main task is to find proper data in source image and transformation parameters, then reconstruct the target foreground in damaged regions by solving a Poisson equation according to the data and parameters above. In order to guarantee optimal matching and more plausible reconstruction, both target foreground and source foreground are extracted by matting [9] beforehand.

As for background completion phase, since the foreground and background are handled separately, the avoidance of diffusion between foreground and background is necessary. To achieve this goal, we design a novel weighted exemplar-based synthesis algorithm, which produce a new priority map.

A. Poisson-based Foreground Completion

A target image T and a source image S are taken as inputs, where T is the damaged image with critical parts missing and S provides gradient information for foreground completion.

1) *Optimal Matching:* To achieve the optimal transformation parameters, a dilation or erosion process is applied to the two alpha mattes obtained from matting process to get the corresponding boundary curves showed in fig. 2. Then we formulate an energy function to measure the similarity between the boundary curves:

$$E(U) = \sum_i \left\| dist(P_t(i), C_s(U)) \right\|^2 \qquad (1)$$

Where $E(U)$ evaluates the curve similarity between curve C_t and curve $C_s(U)$ in a $n \times n$ bounding box showed in fig. 2, C_t and $C_s(U)$ belong to target and source foregrounds, respectively. $dist(P_t(i), C_s(U))$ is the shortest distance from point $P_t(i)$ on C_t to $C_s(U)$, where i is the index of the points on C_t in bounding box and U denotes the set of the transformation parameters, Let $U = (X, Y, Scale, Rotation)$, it contains four parameters: the horizontal and vertical offsets, scaling factor and rotation factor of source image relative to the target image. By minimizing equation (1), we can get the optimal matching parameters:

$$u = (x, y, s, r) = \arg\min_U E(U) \qquad (2)$$

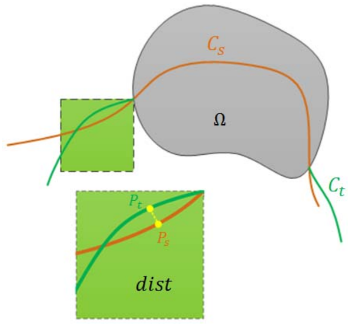

Fig. 2 Optimal matching for boundary curves. Red curve C_s and green curve C_t are the boundary curves of source foreground and target foreground, respectively.

2) *Guided Poisson Foreground Reconstruction:* In this section, we detail the Poisson foreground reconstruction process under a guidance of gradient vector field. In order to make the reconstructed foreground more coherent, we adjust the color of source foreground by employing a histogram specification technique according to the target foreground beforehand, although it is not required.

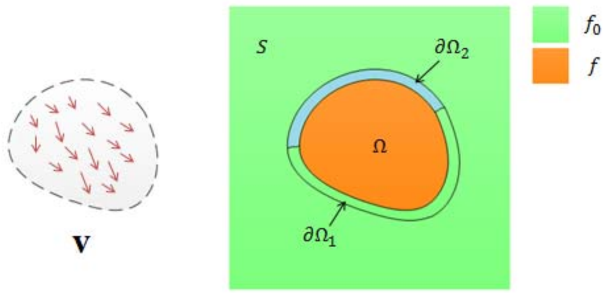

Fig. 3 Guided interpolation notations, unknown function f interpolates into origin function f_0 in domain Ω, under a guidance of gradient field $\mathbf{v}$.

For simplicity, we consider single channel. Fig. 3 indicates the notations: let S be the whole image definition domain, and Ω the damaged region with boundary $\partial\Omega_1$ and $\partial\Omega_2$, where $\partial\Omega_1$ lies between target foreground and damaged region, and $\partial\Omega_2$ lies in damaged region. Being f_0 the known function on S, f the reconstructed function on Ω under a guidance of vector field $\varphi(\mathbf{v})$, where $\mathbf{v}$ is the gradient of source foreground adjusted after histogram specification and transformed according to $u=(x,y,scale,rotation)$.

In order to produce visually plausible results, the reconstructed gradient should be closest to the one of source foreground, and we pose the foreground completion process as an optimization problem with a guided field $\varphi(\mathbf{v})=P(x,y)i+Q(x,y)j$ similar to [7]:

$$J=\iint_{\Omega}\|\nabla f-\varphi(\mathbf{v})\|^2 d\Omega \tag{3}$$
$$\text{s.t. } f|_{\partial\Omega_1}=f_0|_{\partial\Omega_1}, f|_{\partial\Omega_2}=f_0|_{\partial\Omega_2}+\delta$$

Where ∇f denote the gradient of function f and δ is a constant to adjust the values of $\partial\Omega_2$. In order to simplify the derivation, we adopt L2-norm. The minimum of functional J is achieved when f satisfies the associated Euler-Lagrange equation, which is a Poisson equation:

$$\frac{\partial^2 f}{\partial x^2}+\frac{\partial^2 f}{\partial y^2}=\frac{\partial P}{\partial x}+\frac{\partial Q}{\partial y} \tag{4}$$
$$\text{s.t } f|_{\partial\Omega_1}=f_0|_{\partial\Omega_1}, f|_{\partial\Omega_2}=f_0|_{\partial\Omega_2}+\delta$$

A more simplified version is:

$$\Delta f=div\varphi(\mathbf{v}) \tag{5}$$
$$\text{s.t. } f|_{\partial\Omega_1}=f_0|_{\partial\Omega_1}, f|_{\partial\Omega_2}=f_0|_{\partial\Omega_2}+\delta$$

Where $\Delta=\partial^2./\partial x^2+\partial^2./\partial y^2$, $div\boldsymbol{\varphi}(\mathbf{v})=\partial P/\partial x+\partial Q/\partial y$ is the divergence of $\varphi(\mathbf{v})$, and $\varphi(\mathbf{v})$ means some adjustments to $\mathbf{v}$. For convenience, we simply set $\varphi(\mathbf{v})=\mathbf{v}$, and satisfying results are already obtained with this very simple selection.

For digital image, minimization of equation (3) can be directly discretized using the underlying discrete pixel grid. For each pixel p in S, let N_p be its 4-connected neighbors, $<p,q>$ a pixel pair such that $q\in N_p$, and f_p the gray value of pixel p. Compared with equation (5), equation (3) can be discretized more easily:

$$\min_{f|_\Omega}\sum_{\langle p,q\rangle\cap\Omega\neq 0}\left(f_p-f_q-\mathbf{v}_{pq}\right)^2 \tag{6}$$
$$\text{s.t. } f|_{\partial\Omega_1}=f_0|_{\partial\Omega_1}, f|_{\partial\Omega_2}=f_0|_{\partial\Omega_2}+\delta$$

For $p\in\partial\Omega_1$, $f|_{\partial\Omega_1}=f_0|_{\partial\Omega_1}$, and $p\in\partial\Omega_2$, $f|_{\partial\Omega_2}=f_0|_{\partial\Omega_2}+\delta$, when $p\in\Omega$, obviously, the following simultaneous linear equation has the same approximate value with equation (6):

$$|N_p|f_p-\sum_{q\in N_p\cap(\partial\Omega_1\cup\partial\Omega_2)}f_{0q}-\sum_{q\in N_p\cap\Omega}f_q=\sum_{q\in N_p}\mathbf{v}_{pq} \tag{7}$$

Where $|N_p|$=4 when Ω doesn't extend to the outmost boundary of S, otherwise $|N_p|<4$. Here, we can see that the left term and right term in equation (7) are similar to ∇f and $\varphi(\mathbf{v})$ in equation (3), respectively.

In conclusion, minimizing equation (3) means seeking a function f whose gradient is closest to the one of the adjusted source foreground. As for color image, we minimize equation (3) in R, G, B channel independently.

Through the use of layer-divided image completion scheme, our algorithm breaks through the limitation of color similarity in [7] and the reconstructed color will not distort anymore. Moreover, we can get a group of coherent completion foregrounds as we desired as parameter δ changing, while [7] can produce only one image. Comparatively speaking, our algorithm is more flexible and robust.

B. Exemplar-based Background Completion

After target foreground completion, large region of damaged background still exists. For without loss of generality, we adopt notations similar to [2]: Φ, Ω, $\partial\Omega$ denote source region, damaged region and boundary of Ω, respectively.

1) Priority Map

For each unfilled pixel $p\in\partial\Omega$, the priority function $P(p)$ in [2] is defined as the product of two terms:

$$P(p)=C(p)\times D(p) \tag{8}$$

Where $C(p)$ and $D(p)$ are confidence term and data term, respectively. And they are defined as follow:

$$C(\mathrm{p})=\frac{\sum_{q\in\Psi_p\cap\Phi}C(q)}{|\Psi_p|} \tag{9}$$

$$D(p)=\frac{|\nabla I_p^{\perp}\cdot\mathbf{n}_p|}{\alpha} \tag{10}$$

Where Ψ_p denotes a patch centred at pixel p, and $\nabla I_p^{\perp}$, $\mathbf{n}_p$, α are the isophote vector, a unit vector orthogonal to $\partial\Omega$, a normalization factor (e.g. $\alpha=255$ for gray-level image) respectively.

Though work well in linear structure recovery, Criminisi's algorithm [2] may produce incoherent results to the remaining damaged regions directly, as patches in foreground and background diffuse each other, and Cheng et al. [10] pointed out that $C(p)$ defined in [2] decreases exponentially. In order to avoid patch diffusion, we devise a new priority map. For more balanceable and controllable, we reformulate the priority function as a summation of three terms:

$$P(p)=a\cdot C(p)+(1-a)\cdot D(p)+b\cdot dist(p) \tag{11}$$

Where a is a balance parameter between $C(p)$ and $D(p)$, and b is used to adjust the influence of distance term $dist(p)$, which indicates the shortest distance from point p to boundary $\partial\Omega_1$. The larger $dist(p)$ is, the higher filling priority point p gets, so this formulation not only ensures the continuity of structures, but also avoids patch diffusion between foreground and background. a and b are empirically set to 0.7 and 0.001.

Finally, we combine the completed foreground and background together to produce a complete image. To make

Fig. 4 Completion results and comparisions. From left to right: target images with corresponding source images inplanted in corner, Criminisi's results, Hays's results, Perez's results, and our results.

the fusion more natural and visually plausible, a smooth operation is applied to erase the sawteeth along the seam between completed foreground and background through a weighted average process.

III. Experiments And Analysis

To demonstrate the effectiveness of our proposed algorithm, we compare it with the most competitive ones: Criminisi's method [2], Hay's one [6] and Perez's one [7], on several test images with critical information missing.

Fig. 4 shows the completion results of these four methods, and we can see that, given damaged target image and source image, our algorithm can get more excellent results. Criminisi's method leads to seriously unreasonable results in the damaged regions for incorrect inference, this is due to the lack of enough similar patches and indeterminacy of the structure tendency about critical parts. To compare with Hay's method and Perez's method, we use the same target images, source images and geometric transformation parameters to perform these tests. As for Hay's method, both foreground and background completions are seriously inconsistent although optimal matching and edge smoothness techniques are applied. And as for Perez's method, the background completion produce relative coherent result, while the color of completed foreground distort heavily, in general, this method lead to poor results unless backgrounds in both target and source images have similar color. Observing the results by our method carefully, we can easily find that both foregrounds and backgrounds of the damaged target images are completed quite naturally and reasonably whether from the perspective of color coherence or structure smoothness.

IV. Conclusions

In this paper, a novel layer-divided image completion scheme is proposed to restore damaged region of target image with critical region missing, and the foreground completion is simulated as a guided diffusion process by solving a Poisson equation. Better performance of our algorithm is achieved mainly due to the employment of layer-divided completion scheme and the combination of Poisson surface reconstruction technique, which effectively avoid blocking effect caused by copying patches, meanwhile preserve the sharpness of edges.

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References

[1] M. Bertalmio et al., "Image inpainting", *in Proceedings of the 27th annual conference on Computer graphics and interactive techniques*, pp. 417-424, 2000.

[2] A. Criminisi et al., "Region filling and object removal by exemplar-based image inpainting", *IEEE Transactions on Image Processing,* vol. 13, pp. 1200-1212, 2004.

[3] N. Komodakis et al., "Image completion using efficient belief propagation via priority scheduling and dynamic pruning", *IEEE Transactions on Image Processing,* vol. 16, pp. 2649-2661, 2007.

[4] Y. Liu et al., "Exemplar-based image inpainting using multiscale graph cuts", *IEEE Transactions on Image Processing* , vol. 22, pp. 1699-1711, 2013.

[5] J. Sun et al., "Image completion with structure propagation", *in ACM Transactions on Graphics (ToG)*, vol. 24, pp. 861-868, 2005.

[6] J. Hays et al., "Scene completion using millions of photographs", *in ACM Transactions on Graphics (TOG)*,vol. 26, pp. 4, 2007.

[7] P. Pérez et al., "Poisson image editing", *in ACM Transactions on Graphics (TOG)*, vol. 22, pp. 313-318, 2003.

[8] C. Tang et al., "Sample-based image completion using structure synthesis", *ICIP*, vol. 24, pp. 1115-1123, 2013.

[9] A. Levin et al., "A closed-form solution to natural image matting", *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 30, pp. 228-242, 2008.

[10] W.-H. Cheng et al., "Robust algorithm for exemplar-based image inpainting", *in Proceedings of the International Conference on Computer Graphics, Imaging and Visualization,* 2005.