J. Vis. Commun. Image R. 40 (2016) 312–323

Contents lists available at ScienceDirect

J. Vis. Commun. Image R.

journal homepage: www.elsevier.com/locate/jvci

Structure-aware image inpainting using patch scale optimization ☆

Zhihua Chen [a], Chao Dai [a], Lei Jiang [a], Bin Sheng [b,*], Jing Zhang [a], Weiyao Lin [b], Yubo Yuan [a,*]

[a] Department of Computer Science and Engineering, East China University of Science and Technology, Shanghai 200237, China
[b] Department of Computer Science and Engineering, Shanghai JiaoTong University, Shanghai 200240, China

ARTICLE INFO

Article history:
Received 9 September 2015
Revised 6 March 2016
Accepted 29 June 2016
Available online 7 July 2016

Keywords:
Image inpainting
Texture synthesis
Local structure multiplier
Patch scale optimization

ABSTRACT

Image inpainting is widely used in many image processing applications such as image stitching, image editing and object removal. The main challenge stems from producing visually plausible results after reconstruction. Most of the image inpainting algorithms cannot maintain structure continuity and texture consistency precisely. To address this problem, we propose a robust exemplar-based inpainting algorithm. Firstly, we present local structure multiplier to contain sufficient structure information in the priority function which ensures the structure continuity. Secondly, we combine color feature and space distance between two patches to search for the optimized patch to avoid texture inconsistency. At last, we calculate the average pixel difference between two patches under each candidate scale, we select the scale which the minimal average pixel difference is to be the optimized scale. We copy the target patch with the optimized patch. Extensive experiments show the effectiveness of the proposed method.

1. Introduction

Image inpainting is to get a damaged image inpainted as physically plausible and visually pleasing as possible. It has a wide range of applications, such as image restoring from scratches and text overlays, object removal, and image editing [1].

Many image inpainting algorithms have been proposed in order to address this problem. The exemplar-based technique is quite an inspiring concept that many corresponding algorithms have been proposed under the exemplar-based framework in [2–6]. But these methods sometimes cannot ensure the structure continuity and texture consistency because the strategy in their algorithms is less effective. To maintain the structure continuity, one image should be inpainted from structure area. While, the priority function in their algorithms do not contain enough structure information, which can be known from their inpainting results. In patch searching process, existing algorithms only use color feature between two patches to search for the optimized patch. Neglecting space distance factor would cause texture inconsistency. In addition, the existing exemplar-based image inpainting algorithms use fixed patch scale during the patch copying process. Due to the irregularity of texture in different unit patches, the fixed patch scale would probably lower the accuracy of inpainting.

When we inpaint one input image, the different result is obtained with different initial location. All existing methods paid their attention on measuring the structure confidence on the fill-front instead of considering the structure continuity. The motivation of this paper is to overcome the problems of structure continuity and texture consistency. The primal goal of proposing the specific multiplier for structure information is to get a better initial inpainting location with enough structure information. We present our strategy respectively on filling order, filling content and filling scale in the inpainting process. We present our local structure multiplier in our priority function. And then we take both color and space distance into consideration in patch searching process to maintain the texture consistency. With the consideration of both color and distance features, we can optimize the patch size for patch searching for inpainting. At last, we explore the influence of multiscale in the level of patches to robust our algorithm. We aim to find the patch with the optimized scale by calculating an average pixel difference between two patches. The details of our algorithm will be explained in Section 3. The outline of our algorithm is demonstrated in Fig. 1.

1.1. Contributions

We list the contributions of this paper as following:

- Filling order: We present our local structure multiplier in priority function to contain more gradient information. It is a sum of gradient magnitude on the source pixels within the target

☆ This paper has been recommended for acceptance by M.T. Sun.
* Corresponding authors.
E-mail addresses: shengbin@cs.sjtu.edu.cn (B. Sheng), ybyuan@ecust.edu.cn (Y. Yuan).

http://dx.doi.org/10.1016/j.jvcir.2016.06.029
1047-3203/

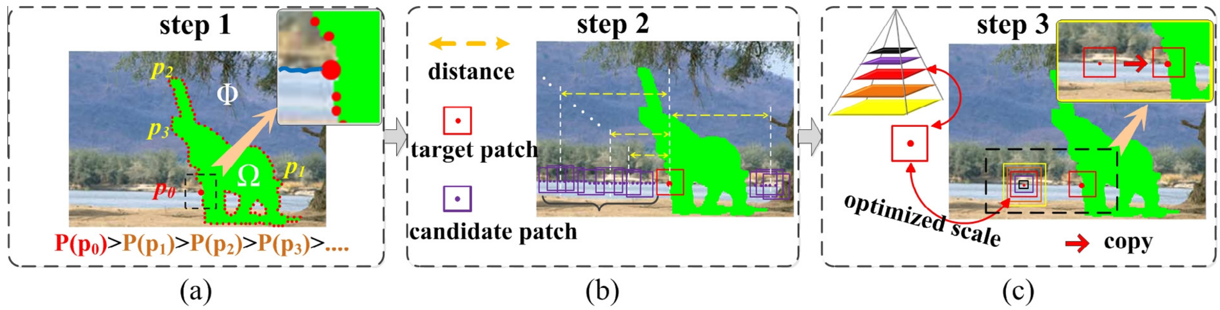

Fig. 1. Outline. (a) Calculate the priority of each pixel on the fill-front and determine the filling order; as $P(p_0) > P(p_1) > P(p_2) > P(p_3) > \ldots$, the point p_0 is selected to be inpainted first due to its largest priority value; (b) search for the optimized patch and determine the filling content considering both color and distance; color feature is used to control the similarity between two patches and distance feature is used to ensure the texture consistency; (c) determine the filling scale by computing the average pixel difference between two patches.

patch. More gradient information leads to larger priority value, the pixel with larger priority value is more probably in structure area. Calculating the priority helps to determine the filling order;

- Filling content: In patch searching process, we consider both color feature and space distance. Color similarity leads to an accuracy patch match while space distance between two patches contributes to texture consistency;
- Filling scale: The optimized scale is obtained from a candidate set. By calculating the average difference of corresponding pixels between target patch and optimized patch in each scale. The scale which the minimal average difference is in is the optimized scale. In this way, we can achieve more accurate inpainting performance.

1.2. Structure

This paper is organized as follows. Section 2 is about the related works. In Section 3, an overview of the proposed algorithm is presented and main content in our inpainting algorithm are introduced including local structure multiplier, geometric distance factor and optimized scale. Some implementing detail and the final experiments and comparisons are demonstrated in Section 4. At last, we conclude our work in Section 5.

1.3. Notations and operators

In order to help the readers to understand the content quickly, we show some notations at the beginning of this section.

- $\mathbf{x}$ or (x,y) or $p(x,y)$–the spatial coordinates (geometry location of each pixel);
- $\mathbf{I}(x,y)$ or $\mathbf{I}'(x,y)$–the color image on $\mathbf{D}$;
- $f(x,y)$ or $\hat{f}(x,y)$–the color value of the pixel (x,y);
- S–the natural scale or grid, such as 5×5, 7×7, or 9×9;
- $E(\hat{f}_S)$–the energy function or the measure to qualify the inpainting function;
- $P(p_i)$–the priority for given $p_i \in \partial\Omega$;
- $d_{\mathcal{F}}(p,q)$–the feature difference between p and q in the inpainting grid and matching patch;
- $d_{\mathcal{G}}(p,q)$–the geometry distance between p and q in the inpainting grid and matching patch;
- ω_1 and ω_2– the weights used to control feature distance and geometry distance;
- $E(\hat{f}_S, \omega_1, \omega_2)$–the energy function with weights ω_1 and ω_2.

2. Related works

Many existing inpainting methods can be classified into two categories: PDE-based image inpainting technique and exemplar-based image inpainting technique.

2.1. PDE-based image inpainting

The first category of the methods introduces partial differential equations or parametric models to diffuse local structures, known as diffusion-based inpainting. This kind of technique was initiated by the work of Bertalmio [7] in the year of 2000, with the use of regularization or diffusion. All PDE-based image regularization methods can be used for image inpainting. In [7], the authors propagate the image from the surrounding neighborhood into the missing area using an anisotropic model. In 2003, Bertalmio et al. proposed a new image inpainting algorithm in [8]. They first consider the image as the combination of two functions with different basic features. Then reconstruct each one of these functions separately with corresponding filling-in algorithms. A fast non-iterative method for image inpainting is proposed in [9] based on a detailed analysis of stationary first order transport equations. Using the fast marching method, it traverses the inpainting part of the image just once while transporting the image values in a coherence direction which is estimated by means of the structure tensor. The method switches continuously between directional and diffusion transport. Motivated by PDE-based techniques, Dobrosotskaya et al. proposed a new image inpainting algorithm in [10], but using more wavelet-based approaches. A method to deal with the wavelet domain inpainting problem was proposed in [11]. The authors use an optimization transfer technique that they take the place of the univariate functional by a bivariate functional via adding an auxiliary variable. To solve Total Variation (TV) inpainting model and weighted TV colorization model, Li et al. [12] proposed to use Chanbolle's dual method. The coefficients are zero in the missing area and a positive constant in the source region. By adding new variables, then the problems can be solved by alternating Chambolles dual method with minimization method. It is fast and easy implemented. Shai Gepshtein and Yosi keller present a framework for image inpainting in [13] that apply the diffusion framework approach to spectral dimensionality reduction. They represent the mapping as a discrete optimization problem, solved by spectral relaxation. In [14], the authors proposed a new image inpainting optimization model. They regard the rows of a DCT matrix as the filters combined with a multi-resolution analysis. In order to analyze the pictures to be inpainted, they have explored the nondecimated wavelet transforms with those filters. In 2014, Fang Li and