STRUCTURE AND TEXTURE IMAGE INPAINTING BASED ON REGION SEGMENTATION

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ABSTRACT

In this paper, we propose a new algorithm for structure and texture filling-in of complex images with missing information. Our algorithm relies on edge-based region segmentation. The segmented regions are used both to reconstruct a structure component and to guide the restoration of a texture component. The contributions of this paper are two-fold. Firstly, we propose an efficient method to prevent the edge-blur in filling-in complex image. Secondly, the texture can be quickly and nicely fixed in our method. Examples on real images show the advantages of our algorithm.

***Index Terms*—**image reconstruction, image region analysis, image restoration, image segmentation, image texture analysis

1. INTRODUCTION

Automatic digital inpainting is a technique which fill-in missing information regions with available information from their surroundings. The technique can be used in old image restoration, special effects (e.g., removal of objects), and coding and wireless image transmission (e.g., recovering lost blocks). The algorithms proposed in the literature fill in missing data from different points of view.

The partial differential equations (PDEs) were utilized for image inpainting [1-3], but it is only fitted for low-resolution images with light scratches or little areas and the computation is time consuming. The drawbacks of PDEs method for filling-in larger regions are lack of consideration for the extension of image textures. In [4] a new viewpoint for image inpainting was proposed. They converted the traditional 2D image inpainting problem into a reconstruction of 3D scatted point problem using radial basis function (RBF). This approach can restore large smooth areas and be computed quickly by fast solution algorithm. But for large variation region, the approach suffers from its origin in the isotropic character of RBF. On the other hand, in order to remedy the results of PDEs algorithms for larger regions, the concept of local texture analysis has been considered by several researchers [5–7]. They analyzed the textures of adjacent zones and upgraded the inpainting algorithms to promote the performance of image inpainting. Nevertheless, this approach was failed to ensure the continuum of the edges and the synthesis algorithm is time consuming because it must compute the entire image. M. Bertalmio [8] decomposed an image into structure and texture components and restored them separately. This method can not restore complex image, because of the drawback of the used structure and texture inpainting algorithms.

We believe that, the information used to restore missing information areas should correspond with the unknown area, that is, the whole image should be segmented into different regions and restore these regions separately. And we also believe that, both structure and texture should be restored in a good inpainting algorithm.

The rest of this paper is organized as follows: we present the main steps of the algorithm in section 2. Section 3 concentrates on image decomposition. Section 4 concentrates on region segmentation. Section 5 describes our structure reconstruction method. Section 6 describes our adaptive texture restoration method. The experiment results are given in section 7. Finally, section 8 draws conclusions and outlines future work.

2. ALGORITHM OVERVIEW

Our algorithm consists of five main steps, (Figure 1): 1) image decomposition; 2) edge-based region segmentation; 3) structure reconstruction based on normalized basis function (NRBF); 4) texture restoration based on adaptive texture matching; 5) adding back those two sub-images.

The input to our algorithm is an image with missing areas. In this paper, we assume that the missing areas are already detected.

In the first step, an image is decomposed into structure and texture components with total variation minimization and oscillating patterns algorithm [9]. This decomposition algorithm produces images that are very well suited for the image structure reconstruction and texture synthesis techniques described in the following.

In the second step, we try to segment the structure and texture image into different regions according to their edges. The purpose of region segmentation is to ensure that the segmented regions in the structure component u are smooth enough for NRBF surface reconstruction and, in the texture component v , different texture belong to different segmented regions, that is, the searching region is small when implement texture synthesis. Fortunately, we observed

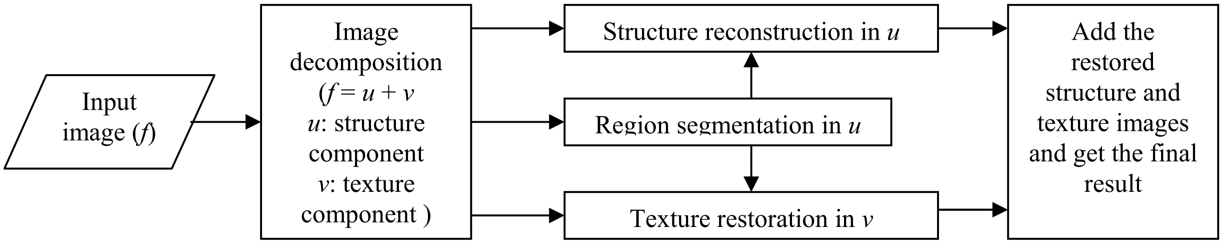


Fig. 1. Algorithm outline

that, in most situations, the segmented regions in both structure and texture image are the same. Therefore, we only need to segment the structure image based on edges. However, edge information is missing in the hole. In order to segment a structure image, we have to connect the broken edges as accurately as possibly. This can be achieved with the help of tensor voting [10].

In the third step, we simply used NRBF surface interpolation to restore the structure image in every region because the segmented regions are smooth enough. Therefore, the 2-dimension image inpainting problem is transformed into 3-dimension surface reconstruction problem. The suitable choose is radial basis function (RBF). However, in order to enhance the universality of our algorithm, NRBF was used.

In the forth step, an adaptive texture matching is used to synthesize the missing texture information in each region because the same texture belong to the same region. In our algorithm, the searching area for a matching block is not the whole image but a segmented region, that is, the missing texture information can be quickly and nicely fixed.

Finally, in the firth step, the image is reconstructed adding back these two sub-images.

3. IMAGE DECOMPOSITION

In this section, we review the image decomposition approach proposed in [11].

Definition 1. Let G denote the Banach space consisting of all generalized functions v which can be written as:

$$v(x,y) = \partial_x g_1(x,y) + \partial_y g_2(x,y), \quad g_1, g_2 \in L^\infty(R^2). \tag{1}$$

Induced by the norm $\|v\|_*$ defined as the lower bound of all L^∞ norms of the functions $|\vec{g}|$ where $|\vec{g}| = (g_1, g_2)$, $|\vec{g}(x,y)| = \sqrt{g_1(x,y)^2 + g_2(x,y)^2}$ and where the infimum is computed over all the decompositions of v.

Meyer showed that if the v component represents texture or noise, then $v \in G$, and proposed the following new image restoration model:

$$\inf_u E(u) = \left\{ \int |\nabla u| + \lambda \|v\|_*, \ f = u = v \right\}. \tag{2}$$

where $f : R^2 \to R$ be a given observed image, $f \in L^2(R^2)$. u is a true image.

Meyer proved that for small λ the model will remove the texture. Inspired by (2), the following minimization problem is the one proposed in :

$$\inf_{u,g_1,g_2} \left\{ \begin{aligned} G_p(u,g_1,g_2) &= \int |\nabla u| \\ &+ \mu \int \left[\left(\sqrt{g_1^2 + g_2^2}\right)^p dxdy \right]^{\frac{1}{p}} \\ &+ \lambda \int \left| f - u - \partial_x g_1 - \partial_y g_2 \right|^2 dxdy \end{aligned} \right\}. \tag{3}$$

where $\lambda, \mu > 0$ are turning parameters, and $p \to \infty$.

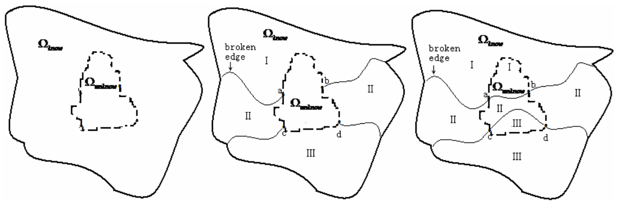
For $p = 1$, as used in this paper, solving equations (3), we can get u, g_1, g_2 and hence v.

4. REGION SEGMENTATION

Assuming, there was an image with a damaged region Ω_{unknow} and the correlative region Ω_{know} (Figure 2(a)).

The follow steps showed how to segment the large variation region (Ω_{unknow} and Ω_{know}) into smooth regions.

1). Detect edges of region Ω_{know} which would pass through the damaged region (Ω_{unknow}). And segment Ω_{know} based on the detected edges. Supposing the detected edges were a, b, c and d and the segmented regions were Ⅰ, Ⅱ and Ⅲ (Figure 2(b)).
2). Find the broken edges that should be connected according to their color relation, direction and position. Supposing the edges found to be connected were a, b and c, d.
3). Connect the broken edges that should be connected



(a) (b) (c)

Fig. 2. Region segmentation

based on the tensor voting algorithm [9]. In Figure 2(b), edges a, b and c, d should be connected respectively.

4). Segment Ω ($\Omega = \Omega_{unkonw} + \Omega_{know}$) relying on connected edges. Therefore, the region Ω was segmented into Ⅰ, Ⅱ and Ⅲ (Figure 2(c)).

5. STRUCTURE RECONSTRUCTION BASED ON SEGMENTED REGIONS

Given a set of distinct nodes $X = \{\mathrm{x}_i\}_{i=1}^{N} \subset R^3$ and a set of function values, $\{f_i\}_{i=1}^{N} \subset R$ find an interpolant $s : R^3 \to R$ such that

$$s(\mathrm{x}_i) = f_i, i = 1, \cdots, N. \quad (4)$$

The space $BL^{(2)}(R^3)$ is equipped with the rotation invariant semi-norm defined by :

$$\|s\|^2 = \int_{R^3} s_{xx}^2(\mathrm{x}) + s_{yy}^2(\mathrm{x}) + s_{zz}^2(\mathrm{x}) + 2s_{xy}^2(\mathrm{x}) + 2s_{zx}^2(\mathrm{x}) + 2s_{yz}^2(\mathrm{x}) d\mathrm{x}. \quad (5)$$

This semi-norm is a measure of the energy or "smoothness" of functions: functions with a small semi-norm are smoother than those with a large semi-norm. The smoothest interpolation has the simple form:

$$s(\mathrm{x}) = p(\mathrm{x}) + \sum_{i=1}^{N} \lambda_i \varphi(|\mathrm{x} - \mathrm{x_i}|). \quad (6)$$

where $p = c_1 x + c_2 y + c_3 z + c_4$ is a linear polynomial, and $|\cdot|$ is the Euclidean norm of R^3.

In order to enhance the universality of our algorithm, NRBF [11] ($\varphi(|\mathrm{x} - \mathrm{x_i}|) = |\mathrm{x} - \mathrm{x_i}| \Big/ \sum_{j=1}^{N} |\mathrm{x} - \mathrm{x_j}|$) was chosen.

An arbitrary choice of coefficients λ_i in Equation (4) will yield a function s that is not a member of $BL^{(2)}(R^3)$. The requirement that $s \in BL^{(2)}(R^3)$ implies the orthogonality or side conditions:

$$\sum_{i=1}^{N} \lambda_i = \sum_{i=1}^{N} \lambda_i x_i = \sum_{i=1}^{N} \lambda_i y_i = \sum_{i=1}^{N} \lambda_i z_i = 0 \quad (7)$$

These side conditions along with the interpolation conditions of Equation (4) lead to a linear system. Solving this linear system determines coefficients that specify the NRBF and hence $s(x)$.

6. ADAPTIVE TEXTURE RESTORATION

In generally texture synthesis approaches, the size of seed-block is fixed and the searching area is the whole image. These introduce two drawbacks:

1). There would be mistake when an image contains many different textures. Because different textures should choose different sizes of seed-block.

2). It will be time consuming to search the fittest filling-in block when the image is large.

In order to overcome these drawbacks, a texture adaptive synthesis based on segmentation was proposed. It is only need to search the fittest filling-in block in the corresponding segmented region. Therefore, it is suit for large image texture synthesis. And our approach can choose the size of seed-block automatically according to the variation of the region in restoration different segmented regions.

The variation of region is measured as following.

$$\bar{x}^k = \sum_{\forall i} \sum_{\forall j} x_{ij} \Big/ N^{\mathrm{k}}, \quad (i,j) \in \Omega_{\mathrm{know}}^{\mathrm{k}}. \quad (8)$$

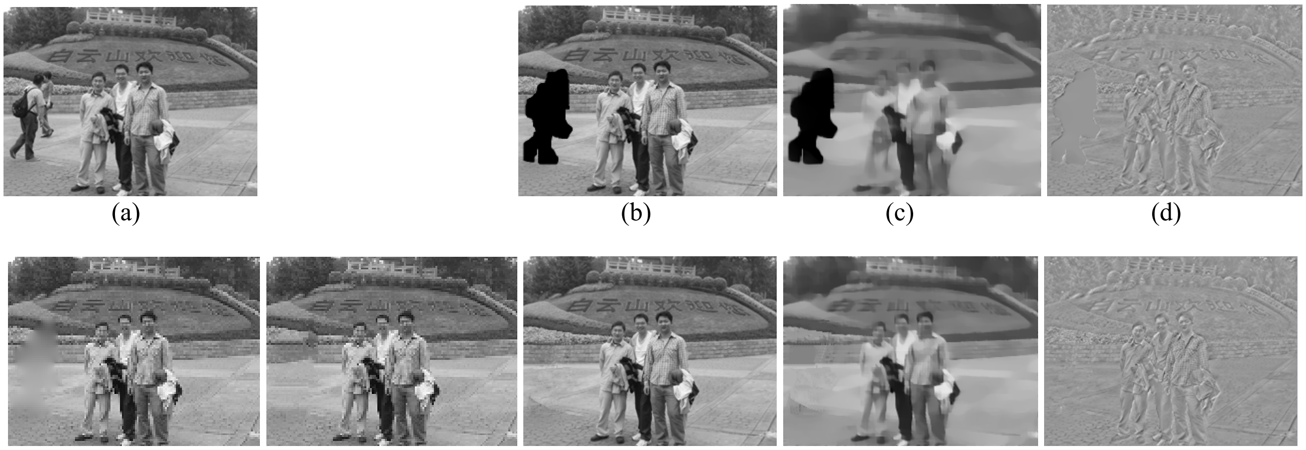
$$\mathrm{var}^{\mathrm{k}} = \sum_{\forall i} \sum_{\forall j} (x_{ij} - \bar{x}^k)^2 \Big/ N^{\mathrm{k}}, \quad (i,j) \in \Omega_{\mathrm{know}}^{\mathrm{k}}. \quad (9)$$

where Ω_{know}^{k} is the available domain in the *k*-th region. N^k is the number of know points in the *k*-th region. $\bar{x}^k$ is the mean of know points in the *k*-th region. var^k is the variation of know point in the *k*-th region.

The larger the value of var^k is, the more complication the texture is. Therefore, the size of block should be smaller. And, for the purpose of reducing error diffusion, the block which has more know points should be restored first.

7. RESULTS

We now present a real result (removal of unwanted people) from our algorithm and compare with the case when the



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

(e) (f) (g) (h) (i)

Fig. 3. Object removal. Results from different algorithms and the progress of our algorithm with $\lambda = 0.05$, $\mu = 0.01$ are shown. (a) is an original image and (b) is the image with selected region (black region) to be filled in. Then (b) is decomposed into a structure image (c) and a texture image (d). These two images are reconstructed via structure reconstruction and adaptive texture synthesis proposed in our paper, respectively, (h), (i). (g) the final result of our algorithm. For comparison, (e) is the result from RBF inpainting algorithm [4] and (f) is the result from algorithm proposed in [6].

image is not decomposed prior to filling-in. In image decomposition, the damaged area will not be considered. In Figure 3, (b)-(d) and (g)-(i) showed the filling-in process of our algorithm. The main component of structure was contained in (c) and the main component of texture was contained in (d). The missing area in both structure and texture image were naturally restored (Figure 3(h) and (g)). Final result (Figure 3(g)) of our method showed that the image was restored without detection. But the result (Figure 3(e)) from RBF image inpainting was blurry, which was because the large variation surface could not be reconstructed by RBF, and the result (Figure 3(f)) from texture synthesis can be easily detected, which is because the pure texture synthesis can not ensure the connection of the edges especially when there are complex edges.

8. CONCLUSION AND FUTURE WORK

We proposed an algorithm for structure and texture image inpainting based on region segmentation. This algorithm can ensure the edge continuous character, which is one of the most important characters in image inpainting, and make the restored regions less blurry. Additionally, region-segmentation-based structure reconstruction ensures the surface can be nicely reconstructed by NRBF and adaptive texture restoration based on region segmentation can achieve fast and accurate result. Therefore our method is more appropriate to the large damaged regions restoration.

We are currently looking at improved methods for image inpainting, including more accurate segmentation method and compactly supported radial basis function for surface reconstruction.

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