Improved Exemplar Based Texture Synthesis Method for Natural Scene Image Completion

K. Sangeetha[1], Dr. P. Sengottuvelan[2], E. Balamurugan[3]

[1] Department of Computer Applications, Bannari Amman Institute of Technology,

Sathyamangalam, Erode District 638 401, Tamilnadu, India

[2] Department of Information Technology, Bannari Amman Institute of Technology,

Sathyamangalam, Erode District 638 401, Tamilnadu, India

[3]Department of Computer Applications, Bannari Amman Institute of Technology,

Sathyamangalam, Erode District 638 401, Tamilnadu, India

Abstract

Image inpainting or image completion refers to the process of filling in the missing data of an image in a visually plausible way. Given a natural scene input image with selected target regions, both the geometrical property and texture information should be propagated from the known parts of image into the target regions. Exemplar-based model fills the target region using the source exemplars in the known parts of image. Many works on this subject have been proposed these recent years. In this paper, we present an inpainting method based on the improved exemplar-based texture synthesis technique which includes image gradient information during the inpainting process. A comparison with some existing methods on different natural images shows the strength of the proposed approach.

Keywords: *Image Inpainting, exemplar based, Texture synthesis, image completion, Partial Differential Equation (PDE)*

1. Introduction

Image inpainting is an iterative method for repairing damaged pictures or removing unnecessary elements from pictures. This activity consists of filling in the missing areas or modifying the damaged images in a non-detectable way by an observer not familiar with the original images [1]. Applications of image inpainting range from restoration of photographs, films and paintings, to removal of occlusions, such as large unwanted regions, superimposed text, subtitles, stamps and publicity, from images. In addition, it is of significant importance in restoration of precious work of arts, calligraphies, and paintings in the digital museum with image inpainting technique [13].A number of algorithms address this image filling issue [2], [3], [7], [8], [12]; these image inpainting techniques fill holes in images by propagating linear structures (called isophotes in the inpainting literature) into the target region via diffusion. They are inspired by the partial differential equations (PDE) of physical heat flow, and work convincingly as restoration algorithms.

The PDE-based algorithm does not perform well for texture dominated pictures. For such cases the exemplar based algorithm is used instead [5], [10], [11]. Given a texture sample, the texture synthesis problem consists in synthesizing other samples from the texture. The usual assumption is that the sample is large enough to capture the stationarity of the texture. There have been many works extending texture synthesis to inpainting.

In the seminal paper [4], the authors have presented a simple yet effective nonparametric texture synthesis method based on local image patches. The texture is modeled as a Markov Random Field (MRF) by assuming that the probability distribution of brightness values for one pixel given the brightness values of its spatial neighborhood is independent from the rest of the image. The neighborhood is a square window around the pixel and its size is fixed by hand. The input of the algorithm is a set of model image patches and the task is to select an appropriate patch to predict the value of an unknown pixel. This is done by computing a distance measure between the known neighborhood of an unknown pixel and each of the input patches. The distance is a sum of squared differences (SSD) metric.

The authors of [5] proposed an extension of Efros and Leung's method, with two improvements. The first one concerns the order in which the pixels are synthesized. Indeed, a system for assigning priorities is used (assigning priorities to the pixels was also proposed in [6]. The priority order at a pixel is the product of a confidence term, which measures the amount of reliable information surrounding the pixel, and a data term, that encourages linear structures to be synthesized first. The second improvement is a speed-up process. Contrary to the original method in [4], when synthesizing a pixel, not only the value of this pixel is inpainted in the output image (using the patch that gives the smallest distance metric), but all the pixels in its neighborhood that have to be inpainted are filled in.

With these algorithms, the gap will be filled with non-blur textures, while at the same time preserve and extend the linear structure of the surrounding area. These algorithms, however, have some problems: firstly, it merely adopts a simple priority computing strategy without considering the accumulative matching errors; secondly, the matching algorithm for texture synthesis only uses the color information; thirdly, the filling scheme just depends on the priority disregarding the similarity. As a result of lacking robustness, their algorithm sometimes runs into difficulties and "grows garbage". To solve these problems, we propose an enhanced exemplar-based inpainting algorithm.

2. Exemplar-based Texture Synthesis Algorithm

The basic conception of exemplar based model is copying information from the source exemplar in the known parts of image into the target region [14]. The selection of the source exemplar is determined by similarity function. Similarity is computed by the difference between pixels in two exemplars. The input of the completion algorithm is an image which contains the masked target region D, and the output is a completed image with the region D filled.

In this paper, an improved exemplar-based image completion model is proposed. The improved model follows the basic conception in [5], and it does not need user's interaction. When the removing or restoring target region is selected, it processes image automatically. The whole image domain is Ω, the removing or restoring target region domain is D, and image information in Dc $(\Omega - D)$ is known; the basic unit of synthesis is the exemplar Ψ. Image completion generates image information in D according to the information in Dc, and the whole exemplar Ψ is copied every time. When there are different kinds of texture patterns in image, the linear structure is restored firstly [9], and then the proper exemplar could be found and copied. The difference between exemplars is used to weigh the exemplar similarity, and the gradient information is often adopted. When a textured image is processed, the geometrical difference between exemplars should be considered. So a composite similarity function which is determined by gradient information is used to compute the exemplar similarity. Then the proper textured exemplar could be found in the textured image completion.

3. The Proposed improved Exemplar based Texture Synthesis Algorithm

In [3], the texture image is inpainted with the algorithm from [4]. This algorithm can be using the method from [5]. Indeed, setting an inpainting order (depending on the edges and the confidence) to the pixels clearly leads to better results. Furthermore, copying an entire patch instead of only one pixel is faster. We here propose some improvements to this algorithm and the modified algorithm has the following properties:

- Properly completes the natural scene image when there are different kinds of texture patterns;
- Preserves the linear structure property;
- Finds the most similar exemplar in the textured image based on gradient information;

3.1 Improvement in Data Term

The first improvement concerns the data term in the priorities of [5]. The data term is defined as

$$D(p) = \frac{|\nabla I^{\perp}(p)|}{\alpha} \quad (1)$$

where $\nabla^{\perp}$ is the orthogonal gradient and a is a normalization factor (equal to 255 for grayscale images). It encourages the linear structures to be synthesized first and depends on the isophotes (contours) that eventually pass by *p*. If we compute this term on the texture image, we will only take into account the small contours and the noise contained in the texture, but not the important edges. Indeed, we can now use the tensors of texture *J*(*p*)

$$J(p) = \sum_{d=1}^{n} \nabla I_d(p) \nabla I_d^T(p), \quad (2)$$

to compute the data term where ∇I_d denotes the gradient image. The eigenvalues at pixel *p* are $\lambda^-(p)$ and $\lambda^+(p)$ and corresponding eigenvectors are $\theta^-(p)$ and $\theta^+(p)$.

Using these notations, the new data term is given by:

$$D(p) = \frac{\lambda^+(p) - \lambda^-(p)}{\alpha}. \quad (3)$$

3.2 Improvement in Search Direction

Another improvement concerns the directions in which the candidate patches are searched for. It can be applied directly to the algorithm from [5]. The idea is to remark that the best patch $\Psi_{\hat{p}}$ for the source patch Ψ_p is probably in the direction of the isophotes (the isophote direction is given by the eigenvector $\theta^-(p)$). We then propose to only look for the candidate patches Ψ_q that verify the following test:

$$\theta^-(p) \cdot \frac{p-q}{\|p-q\|} > 0.9. \quad (4)$$

In the original texture synthesis method, finding the candidate patch $\Psi_{\hat{p}}$ (centered at pixel $\hat{p}$) corresponds to solving

$$\hat{p} = \underset{q \in \bar{\Omega}}{\operatorname{argmin}} \sum_{r \in \Psi_p} M(r)\left(I(r) - I(q+r-p)\right)^2, \quad (5)$$

where *d* is the sum of square differences (SSD) function.

The best patches correspond to the patches that have the smallest associated distance measures. Restricting the direction of the search, eq. (5) becomes:

$$\hat{p} = \underset{q \in \bar{\Omega} | \theta^-(p) \cdot \frac{p-q}{\|p-q\|} > 0.90}{\operatorname{argmin}} \sum_{r \in \Psi_p} M(r)\left(I(r) - I(q+r-p)\right)^2. \quad (6)$$

Note that we compute the distance both on the texture and the structure images because the texture image can sometimes only contain non informative noise. We then finally get the following equation:

$$\hat{p} = \underset{q}{\operatorname{argmin}} \sum_{r \in \Psi_p} M(r)\left(\left(u(r) - u(r')\right)^2 + \left(v(r) - v(r')\right)^2\right), \quad (7)$$

where $r' = r - p + q$.

3.3 Steps in the Proposed Algorithm

1. For all the pixels p of the mask, compute the priorities P (p) =C (p)*D (p) (for the others, $p \in \bar{\Omega}$, P (p) =0). The pixels with higher values of P will be inpainted first.

2. Inpaint the texture image:
(a) Find the pixel $p \in \Omega$ having the highest priority value and that has not been inpainted yet.

(b) Deciding a pixel belongs to a strong Structure or Texture

• if $\lambda^+(p) - \lambda^-(p) < \beta$, then apply texture synthesis to the pixel p using equation (13) (in practice one patch is arbitrarily chosen between the best ones as in [4].

Copy image data from $\Psi_{\hat{p}}$ to Ψ_p for all the pixels of $\Psi_p \cap \Omega$.

• else do not change the pixel value.

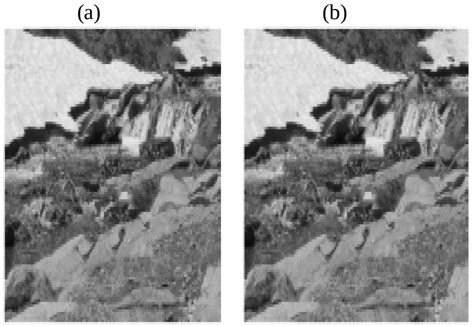
(c) Set $\Omega = \Omega \backslash p$.
(d) Return to (a).

4. Visual Comparison of Experiment Results

The improved exemplar-based algorithm is applied in different kinds of natural scene images to prove its validity in this section. The purpose of image completion is to restore the target region while satisfying the visual perception. The experimental results demonstrate that images generated by our algorithm have satisfactory results compared with Criminisi et al's algorithm [5].

Fig. 1 Reconstruction of lady occluded region of image. (a) Original Image. (b) The target region has been blanked out. (c) The final image in which the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using proposed algorithm.

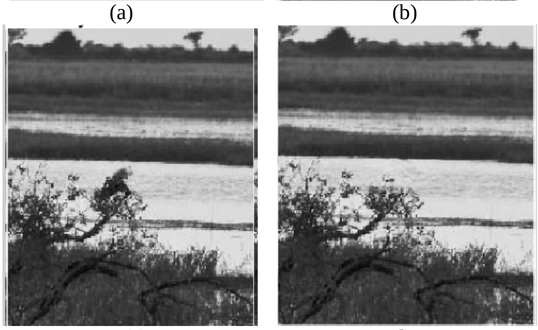
(a) (b)



(c) (d)

Fig. 2 Reconstruction of bird occluded region of image. (a) Original Image. (b) The target region has been blanked out. (c) The final image in which the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using proposed algorithm

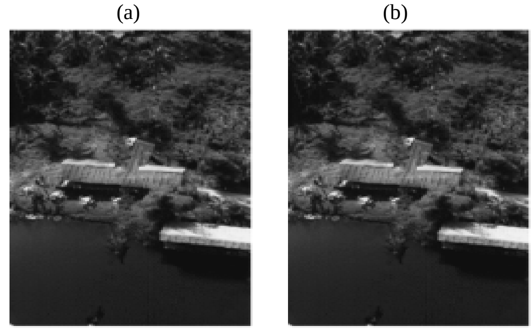
(a) (b)



(c) (d)

Fig. 3 Reconstruction of man occluded region of image. (a) Original Image. (b) The target region has been blanked out. (c) The final image in which the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using proposed algorithm

(a) (b)



(c) (d)

5. Conclusion

In this paper, we have proposed an image inpainting algorithm based on modifying the exemplar-based image inpainting method. The developed algorithm enhances the robustness and effectiveness by including image gradient information during the inpainting process. Several natural scene test images have been used and the results demonstrate that the developed algorithm can reproduce texture and as well as the structure of the surrounding area of the inpainted region. The method proved to be effective in completion of an image which has a hole after removing large objects from it, ensuring accurate propagation of textured pattern. The results obtained are preferable to those obtained by other similar methods. The examples presented demonstrate the effectiveness of the modified algorithm.

References

[1] M. Bertalmio, G. Sapiro, V. Caselles and C. Ballester, "Image Inpainting", Proceedings of SIGGRAPH 2000, New Orleans, USA, pp 417-424, July 2000.

[2] M. Bertalmio, A.L. Bertozzi, and G. Sapiro, "Navier stokes, fluid dynamics, and image and video inpainting",

Proceedings of Conf. Comp.Vision Pattern Rec., Hawai, pp.355–362, Dec 2001.

[3] M. Bertalmio, L. Vese, G. Sapiro, and S. Osher, "Simultaneous structure and texture image inpainting", Proceedings of IEEE conference on Computer Vision and Pattern recognition(CVPR'03), 2003.

[4] A. A. Efros and T. K. Leung, "Texture synthesis by nonparametric sampling," in Proceedings of International Conference on Computer Vision, 1999, pp. 1033-1038.

[5] Criminisi A., Perez P., and Toyama K., "Region filling and object removal by exemplar-based image inpainting", IEEE Trans. Image Processing 9, pp1200-1212, 2004.

[6] Harrison, P, " A non-hierarchical procedure for resynthesis of complex textures", In WSCG Conference Proceedings,2001.

[7] BianRu Li, Yue Qi, XuKun Shen, "An image inpainting method", Ninth International Conference on Computer Aided Design and Computer Graphics, IEEE, 2005.

[8] S. Roth and M. J. Black, "Fields of experts: A framework for learning image priors", Proc. IEEE Comp Vision and Pattern Rec., 2:860-867, 2005.

[9] Sun, J., Yuan, L., Jia, J., and Shum, H, "Image completion with structure propagation", In SIGGRAPH,ACM Special Interest Group on Comp. Graphics and Interactive Techniques, 2005.

[10] A. Criminisi, P. Perez, and K. Toyama, "Region filling and object removal by exemplar- based image inpainting," IEEE Transactions on Image Processing, Vol. 13, 2004, pp. 1200-1212.

[11] Sung Ha Kang, "Mathematical Approaches to Color Denoising and Image Inpainting Problems", Ph.D Thesis, University of California, Los Angeles 2002

[12] Manuel M. Oliveira Brian Bowen Richard McKenna Yu-Sung Chang, "Fast Digital Image Inpainting", Appeared in the Proceedings of the International Conference on Visualization, Imaging and Image Processing (VIIP 2001), Marbella, Spain, September 3-5, 2001

[13] Y. El Glaly, E.Atta, T. Nazmy, and B. Desouky, "Digital Inpainting for Cultural Heritage Preservation", International Conference on Computer Theory and Application, ICCTA, 2006

[14] Ji-Ying Wu And Qiu-Qi Ruan, "A Novel Exemplar-Based Image Completion Model", Journal Of Information Science And Engineering 25, 481-497 (2009).