

## モルフォロジ収縮処理と構造特徴複製に基づく 画像インペインティング

郭 浩<sup>1,2</sup> 西本 卓也<sup>1</sup> 小野 順貴<sup>1</sup> 嵯峨山 茂樹<sup>1</sup>

1 東京大学大学院情報理工学系研究科嵯峨山/小野研究室  
〒113-8656 東京都文京区本郷7-3-1

2 大連海事大学情報学院、〒116026 中国大連海事大学情報学院  
E-MAIL: guo@hil.t.u-tokyo.ac.jp, guohao0512@hotmail.com

**あらまし** 本論文では、モルフォロジ収縮処理と構造特徴複製に基づき、テクスチャ、構造を含む大きい損傷領域に対しても適用可能な新しいインペインティング手法を提案する。この画像インペインティング手法は、テクスチャと構造を既知の小領域から損傷領域に伝播させることによって等輝度線の連続性を保ち、自然でぼけのない画像を出力することができる。いくつかの既存手法との比較実験を通して、小さなスクラッチだけでなく大きな損傷領域においても、本手法が有効に働くことを示す。

**キーワード** 画像復元, 画像インペインティング, モルフォロジ処理, テクスチャ

### Image inpainting method based on morphological erosion and structure feature replication

Hao Guo<sup>1,2</sup>, Takuya Nishimoto<sup>1</sup>, Nobutaka Ono<sup>1</sup>, Shigeki Sagayama<sup>1</sup>

1 Department of Information Physics and Computing, Graduate School of Information Science and Technology, The University of Tokyo  
7-3-1 Hongo Bunkyo-ku Tokyo, Japan, 113-8656

2 School of Computer Science and Technology, Dalian Maritime University, Dalian, China, 116026  
E-MAIL: guo@hil.t.u-tokyo.ac.jp, guohao0512@hotmail.com

**Abstract** The paper presents a new inpainting algorithm applicable for large damaged region including textures and structures based on morphological erosion and structure feature replication. The method can retain the continuity of image isophotes by propagating both texture and structure characteristics information from the known patch into the damaged region, and output a natural-looking and non-blurred image. Through comparative experiments with some existing methods, we demonstrate the effectiveness of the algorithm in removing large objects as well as thin scratches.

**Keywords** image restoration, image inpainting, morphological processing, texture

### 1. Introduction

Image inpainting provides a means to restore damaged regions of an image, such that the image looks complete, natural and logical after inpainting. Image inpainting has a wide range of

applications, such as the restoration of deteriorated images by removing scratches or stains, the removal of text and logos from digital images or the creation of artistic effects.

Since BSCB inpainting algorithm [1] is developed, image inpainting has received

considerable attention and many inpainting methods have been developed. The inpainting problems which those algorithms want to solve are focused on two main classes: 1) To fill in small or long and thin gaps, and 2) To fill in large and thick damaged regions. Several classical interpolation-based inpainting methods [1,2,3,4] belong to the first group. In the BSCB model, the image smoothness information, estimated by the image Laplacian, is propagated along the directions of isophotes. The Total Variational (TV) model [2] and Curvature-Driven Diffusion (CDD) model [3] use an Euler-Lagrange equation coupled with anisotropic diffusion to preserve the directions of isophotes. Their main problem is that both isophotes estimation and information propagation are subject to numerical diffusion, which inevitably leads to blurring of the restoration area. Blurring is undetectable for the restoration of small or long and thin gaps, while it is unacceptable for the restoration of large and thick damaged regions. Several researchers have considered texture synthesis [5,6,7] as a way to fill in large and thick damaged regions. Texture synthesis is suitable to fill in large regions with “pure” textures – different regions of the texture are always perceived to be similar (high correlation). While the damaged regions in many images consists of linear structures and composite textures (multiple textures interacting spatially in many images), and some traditional texture synthesis [5,6,7] have difficulty filling in such domains and say nothing of composite textures.

Image inpainting mostly encounters difficulties for the restoration of large and thick damaged regions with composite textures, for which one can stress out two main issues: 1) how to preserve isophote continuity while propagating both texture and structure characteristics information of the known patch into the damaged region, and 2) how to guarantee the high efficiency and reliability of inpainting. Criminisi et al. developed a inpainting algorithm [8] which can propagate the information from known areas into damaged areas along the isophote directions based on the priorities of isophote directions. It can restore the linear structures features and composite textures in large and thick damaged regions, but sometimes its inpainting results are suspicious and unsatisfactory because it's very difficult to get

and preserve the directions of isophotes properly if composite textures are too complex or the quality of damaged images is poor. We proposed a inpainting model based on morphological erosion and structure feature matching [9], which can restore some structure features (linear contours or curves with small curvature) both for large and thick or long and thin damaged regions. By a series of comparison experiments with Criminisi's inpainting method [8] and BSCB inpainting methods[1], we demonstrate the efficiency and reliability of the proposed inpainting method in removing large occluding objects as well as thin scratches.

## **2. Formulation of the inpainting method**

As for the restoration of large and thick damaged regions, any inpainting methods should answer two main questions: 1) How to fill the damaged regions in order to maintain the efficiency and reliability of inpainting, and 2) What information (structure and texture information) can be chosen reliably for the damaged regions to be restored to remain the isophote continuity. Accordingly our inpainting model includes two parts: 1) Region filling based on morphological erosion, and 2) Restoration based on structure/texture features matching. The process of morphological erosion can imitate the process of manual inpainting with a very high similarity and manual inpainting is considered the most trusted method, so it can guarantee the high efficiency and reliability of inpainting process. The restoration based on structure/texture features matching can preserve isophote continuity by propagating both texture and structure characteristics information of a known patch into the damaged region, and output a complete, natural-looking and non-blurred image.

## **3. Region filling based on morphological erosion**

Morphology is a broad set of image processing operations that process images based on shapes. Dilation and erosion are two fundamental morphological operations. Dilation adds pixels to

the boundaries of objects in an image, while erosion removes pixels from them.

Morphological erosion can be defined as follows. If A is an input binary image and B a structuring element, the erosion of A by B, denoted by  $A \ominus B$ , is given by

$$A \ominus B = \{x \in A \mid (B)_x \subseteq A\} \quad [1]$$

where  $(B)_x$  designates the structuring element B centered at pixel  $x$ . An essential part of the dilation and erosion operations is the structuring element used to process the input image. The center pixel of the structuring element, called the origin, identifies the pixel of interest -- the pixel being processed.

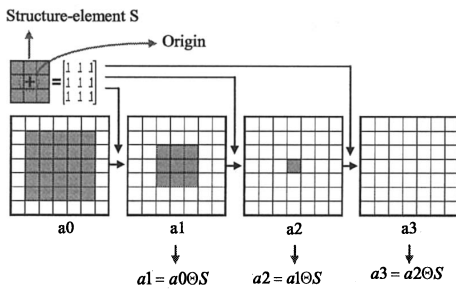


Figure 1. Example of erosion for a binary image

The erosion process is illustrated in Figure 1. By compared image a1 with image a0, we can find one layer pixels of black region is eroded by structure-element S, and the black region in image a1 is shrunk. From this process we can see easily the region filling process of inpainting is more similar with the process of erosion for binary image if we consider black regions in a binary image as damaged regions.

As for gray or color damaged images, if the gray or color information of the unknown pixels can be restored based on information from the neighborhood, inpainting of a damaged region can also be performed using the erosion process. The region filling process based on morphological erosion is illustrated in Figure 2. In the process, a structuring element is iteratively applied to erode the boundary pixels of a damaged region. At each step during this erosion, the boundary pixels covered by structuring element, which specifies the current position of the patch of boundary

pixels to be inpainted, are restored with through structure/texture features matching, as described in the following section. The inpainting process of gray or color images is not completed until all pixels in the region are filled and the structure/texture features in the region are restored.

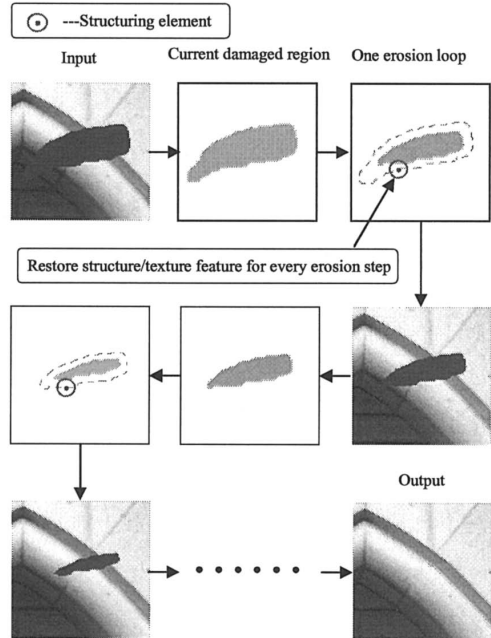


Figure 2. Region-filling process

#### 4. Region Restoration of structure/texture features at every erosion step

It is well-known that almost all interpolation-based inpainting methods are unable to avoid blurring, and are only effective for long thin damaged regions, for which blurring is not perceived easily, while for large and thick damaged regions, blurring is unacceptable. A complete, natural-looking image can be obtained only if the structure/texture features are restored without blurring in order to remain the isophote continuity.

As for the structure/texture features of an image, a definition can be drawn from Figure 3. Texture

features designates gray or color values of different regions which are perceived to be similar or alike, and where each pixel is only related to a small set of neighboring pixels. Structure features are the contour lines of different texture areas, and each pixel has a strong relation to the pixels along the contour line.

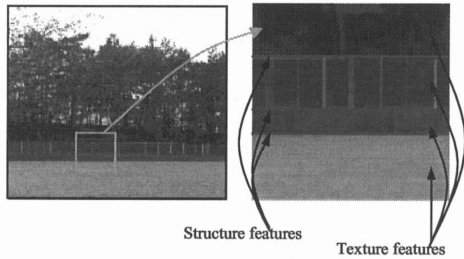


Figure 3. Structure features and texture areas

In manual inpainting, the damaged areas closest to known areas are restored first, which means that only the information in a narrow band along the boundary of the known areas is reliable and has a strong correlation with the information to be restored in the damaged areas. A structure/texture features matching algorithm is introduced in this section. This algorithm, illustrated in Figure 4, can restore some structure features (some ordinary structures such as linear contours or curves with small curvature) both for large and thick or long and thin damaged regions without blurring. It includes two steps as follows:

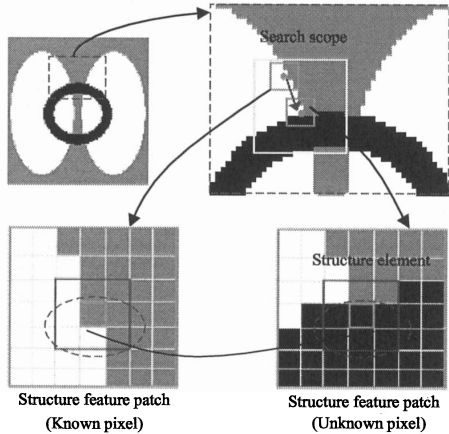


Figure 4. Structure/texture features matching

First, inside a search scope, a patch of each unknown pixels, which is covered by structuring element currently, is compared with that of known pixels left to right and top to bottom, to find the one with maximal similarity based on the Sum of Squared Distance (SSD).

Then, when the structure features patch around a known pixel with maximal similarity (minimal SSD) is found in the search scope, the value of the known pixels in the scope of the structuring element are put into the unknown pixels covered by the structuring element, thus completing one step of inpainting. In this way, the structure/texture features of the known areas are propagated into the damaged areas, and the damaged patch at every erosion step is restored.

## 5. Experimental results and discussion

In order to show the efficiency and reliability of the proposed inpainting method, the method is applied to restore a variety of images and a series of comparison experiments with some existed inpainting methods are preformed. A inpainting testing set of 120 damaged images is also built, which has those characteristics: 1) The testing images have different size and are taken by the writer himself; 2) The testing images are damaged randomly, and include mainly large and thick damaged regions and a little of small or long and thin gaps; 3) By compared with original images (non-damaged), the damaged regions were consisted of linear structures and composite textures (multiple textures interacting spatially in many real and synthetic images).

For image inpainting mostly encounters difficulties for the restoration of large and thick damaged regions with composite textures, and Criminisi's algorithm [8] can restore the linear structures features and composite textures in large and thick damaged regions, we perform a series of comparison experiments with Criminisi's algorithm based on MSE (Mean-Squared Error) of inpainting results versus original images (non-damaged images). Some restoration results are shown in Figure 5, and the analysis of comparison outcomes is shown in Table 1, which shows the high efficiency and reliability of the



proposed inpainting method in removing large occluding objects.



Damaged images    Our method    Criminisi's method[8]

Figure 5. Inpainting results of different methods

Table 1. Analysis of comparison results based on MSE

Inpainting method	Better results	Proportion
Criminisi's method[8]	32	26.67%
Our method	88	73.33%

Another comparison experiment is performed. An image is selected from the inpainting testing set freely, and then the image is damaged with different widths of damaged region. For example there are three different widths of damaged regions (from about 10 pixels to about 40 pixels) in Figure 6. We compared our method with Criminisi's method [8] and BSCB method [1], the outcome is shown in Table 2, and the relation between the width of damaged regions and MSE for the three inpainting methods is shown in

Figure 7. We can see that the proposed method can preserve isophote continuity and restore the linear structures features and composite textures both in large and thick damaged regions and in small or long and thin gaps.



About 10 pixels    About 20 pixels    About 40 pixels  
(a) Images with different width of damaged regions



(b) Inpainting results based on BSCB method[1]



(c) Inpainting results based on Criminisi's method[8]



(d) Inpainting results based on our inpainting method

Figure 6. Inpainting results with three different widths of damaged regions

Table 2. Comparison of the three inpainting methods

Inpainting methods	MSE (10~pixels)	MSE (20~pixels)	MSE (40~pixels)
BSCB's method [1]	2601.37	4044.88	5913.75
Criminisi's method[8]	1973.71	2967.99	4722.87
Our method	1751.24	2374.46	3027.90

Besides the restoration of deteriorated images with scratches or stains, another application of inpainting is objects (text and logos in digital images) deletion, and special effects can be shown. Some examples of object deletion are shown in

Figure 8, and those outputs also look complete, natural-looking and logical.

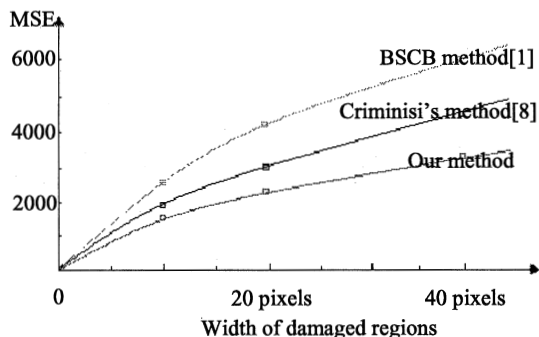


Figure 7. The relation between the width of damaged regions and the value of MSE

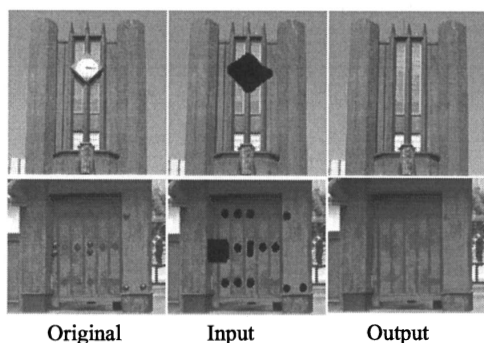


Figure 8: Examples of object deletion and special effects are shown (Output vs. Original)

## 6. Conclusion and future work

As for the restoration of large and thick damaged regions with linear structures and composite textures (multiple textures interacting spatially in many images), most inpainting algorithms published encounter difficulties to preserve image isophote continuity from the known region into damaged region. We presented a inpainting algorithm, which implements the filling of damaged region based on morphological erosion and the matching of structure features. In brief, the method has the following characteristics:

- 1) Based on a structure/texture features matching algorithm, this image inpainting method can

restore some structure features (some ordinary structures such as linear contours or curves with small curvature) both for large and thick or long and thin damaged regions without blurring

- 2) Thanks to the implementation of region-filling based on morphological erosion which can imitate the process of manual inpainting with a very high similarity, the proposed inpainting method can guarantee the high efficiency and reliability of inpainting.

Overall, the presented inpainting method is simple to implement. The method also has some limitations for which more research needs to be done. We plan to work for example on methods to restore complex structure information, such as corners, curves with large curvature, etc.

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