Image Completion Based on Structure Reconstruction and Constraint

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Abstract: Important structures in a large area of a damaged image cannot be satisfactorily repaired by traditional inpainting algorithms. Here, an image completion algorithm based on structure reconstruction and constraint (SRC) is presented to improve the structural coherence of the damaged image. First, the damaged structure of the target image is detected and located. Then, different missing structures are respectively reconstructed. The edge structures are reconstructed by the Euler spiral, which satisfies energy minimization. The corner structure is reconstructed using the intersection of two extended Euler spirals. Finally, the reconstructed structure is used as a constraint condition to modify the priority of the image completion and to guide the texture propagation within the damaged part. The proposed method thereby resolves the problem of the corner structure being unable to be adequately repaired for current image inpainting methods. In addition to preserving the structural continuity, it also effectively avoids texture inconsistency. Experimental results show that the peak-signal-to-noise-ratio values of images recovered by the proposed method increased 3.43 to 12.85 dB. Moreover, compared to the content-aware fill algorithm and Criminisi algorithm, its mean square values decrease by 42.16% to 94.61%. The structure consistency, neighbor texture information coherence, neighbor and visual effect are better than those of the other algorithms. The presented algorithm is thus suitable to repair minor damage, such as a straight line or curving scratch, as well as large area damage, such as object removal in nature scenes and cultural relic images.

Key words: Image completion, structure reconstruction, structural coherence, Euler spiral.

1. Introduction

Image inpainting is an important branch in the image processing field. It can be applied in cultural relic preservation, image encoding, image editing, digital visual effects, and so on. Image inpainting is an ill-posed problem without an explicit special solution. Almost all state-of-the-art image inpainting methods are based on a hypothesis, that is, both the known and unknown pixels in an image have the same statistical property and geometric structure. This hypothesis is transferred to guide the repair process based on different local or global heuristic knowledge of the image to recover an image that is physically viable and has a good visual effect [1].

Current image inpainting methods can be classified into two categories: methods based on diffusion, and methods based on image division [2]. Methods based on diffusion [3]-[5] simulate the skill of manual repair. They use the neighborhood pixels within the known region that is close to the...
unknown region to determine the diffusing content and direction. Then, the repair is applied to the damaged region from outside to inside the image in an iterative manner based on the content of the pixels. These methods are suitable for repairing a relatively small destroyed region, such as a thin-line or curving scratch. The restoration results may appear as an overly smooth phenomenon when processing a large damaged region [2].

The methods based on image division search the matching patch within the known region to replace the damaged patch and implement recovery. However, this method type has two problems: the order of repair and the selection of a good exemplar. Criminisi et al. [6] proposed a repair priority based on image isophotes. This method can preserve the structure well. Nonetheless, the phenomena of structure discontinuity and texture incoherence easily occur for complicated components in an image. To solve the problem of structure discontinuity, Wu et al. [7] improved the restoration effect by adding the compensation of the mean value and penalty term during exemplar searching. However, this method cannot restore the complex corner structure in the image. Wang et al. [8] improved the priority calculating method based on the weight variation of the neighborhood window, and they added the factor of the structure difference during the matching procedure. Their approach has good repair performance with a high computation complexity.

Dong et al. [9] applied the method of matrix interpolation to image repair. The recovered region is blurred for a large area of the damaged image. Xu et al. [10] searched the dynamic-scale matching patch and repaired the damage from the outside to the inside of the image with multiple layers. However, many searches incur large computation costs. Li et al. [11] presented a color-direction patch-sparsity-based image inpainting method using multidirectional features. The restoration results showed good structure continuity for images with a regular direction of structural features. On the contrary, the neighborhood of the repaired region has a low consistency for images with irregular structural feature directions.

Zhang et al. [12] replaced the original isophote-driven priority strategy by color distribution analysis. Their strategy can discriminate texture and structure information well, and it is conducive to preserving the texture coherence and edge continuity. Caselles et al. [13] proposed an exemplar-based image inpainting method using multiscale graph cuts. The destroyed information in the low resolution layer is restored using the feature representation of the original resolution. This method can obtain perfect repair results for a straight-line structure, whereas it shows significant deviations when repairing curve structures. Buyssens et al. [14] introduced a tensor-based data term for better selection of pixel candidates to complete. They also introduced a fast patch lookup strategy and a fast anisotropic spatial blending algorithm to ensure better global coherence of the reconstruction and to reduce typical block artifacts using tensor models.

Pritch et al. [15] presented a method called the shift-map, which rearranges and analyzes known pixel information to determine the position information of pixels and implement image inpainting. He et al. [17] performed image completion by using the statistics of similar patches. This method reduces the time requirement for global optimization. However, incorrect results or inconsistencies with respect to perception by the human vision system may occur because it cannot obtain a dominant offset for images with a low structure repetition and images with a curve structure. In addition, Ružić et al. [18] determined the lookup region of a similar patch based on the texture descriptor, and Deng et al. [19] provided a new separate priority definition to propagate the geometry and then to synthesize the image textures. The phased methodology can recover the image geometry and textures well. Based
on the method in [19], Liu et al. [20] added local feature information to further constrain the priority. The candidate matching patch is constrained by gradient information. An arc promoting method is used to fill in the missing region. The edge smoothness can hence be effectively preserved. To improve the processing speed, a fast method called PatchMatch [21] is combined with the method in [22] and is implemented as the new content-aware fill feature in Adobe Photoshop CS5 [23]. The repair efficiency is improved to the user interaction level.

To solve the problem of the structure information being difficult to preserve for a large damaged area of an image, an image completion method based on structure reconstruction and constraint (SRC) is herein proposed. First, the damaged structure position is detected in the target image. Then, different missing structures are respectively reconstructed. Finally, texture is filled in based on the constraint of the reconstructed structure. The block diagram of the proposed algorithm is shown in Fig. 1.

![Fig. 1. Block diagram of the proposed algorithm.](image)

### 2. Damaged Structure Detection and Reconstruction

Because human eyes are sensitive to high-frequency information that corresponds to structures in an image, the repair quality of the structure has a direct influence on the subjective evaluation. According to gestalt theory, a human will fill in the missing part when observing a damaged or occluded object. In this section, the damaged structure in the target image segmentation is firstly detected based on the human visual characteristic to obtain the position of the damaged structure. Then, the damaged structure is reconstructed to maintain or extend the original structure. There are two major types of structures in an image: the edge and the corner. The edge is a straight line or curved structure. The corner structure is generally considered a point where two-dimensional brightness changes drastically or a point that has a large curvature in the edge curve of the image.

#### 2.1. Damaged Structure Detection

A damaged structure refers to a line broken by a destroyed region or a corner corrupted by a missing part in the target image. It must be detected to determine the position of the damaged
structure. The main structure of the image should be the human object of interest. However, the main structure is often mixed in a considerable amount of background. To reduce the influence of the texture information and background edge, the target image is smoothed by Gaussian blur before detecting the damaged structure.

\[ I_\sigma(x, y) = G(x, y) * I(x, y) \]  
\[ G(x, y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2+y^2}{2\sigma^2}} \]

where “*” means the convolution operation, \(I(x, y)\) is the target image, and \(I_\sigma(x, y)\) is the template obtained after two-dimensional Gaussian smoothing. \(G(x, y)\) is a Gaussian smoothing kernel function. Here, the Gaussian radius is set to five and standard deviation \(\sigma\) is set to two. Fig. 2(a) and Fig. 2(f) are two target images to be repaired. They respectively contain a mountain occluded by a car and a Zhou Dynasty bronze drinking vessel with a broken leg. The corresponding results of Gaussian smoothing are shown in Fig. 2(b) and Fig. 2(g). Then, the blurred images are segmented by a segmentation algorithm, so-called called reconstruction labeling watershed in the color space [24]. The main structures of the target images are hence obtained, as shown in Fig. 2(c) and Fig. 2(h).

To locate the intersection between the damaged structure and known region, and to determine the start and end points of the reconstruction, “T-junctions” are detected from the segmented image using a Kona template [25]. The results of T-junction detection are shown in Fig. 2(d) and Fig. 2(i). Taking Fig. 2(d) as an example, line sections \(L_1, L_2, L_3, L_4, L_5\) are damaged or broken structures, and the corresponding T-junctions points \(a, b, c, d, e\) are positions of damaged or broken structures. The missing structures are grouped into pairs and then reconstructed.

![Fig. 2. Image segmentation and broken structure location.](image-url)
2.2. Damaged Structure Reconstruction

Correct reconstruction of a damaged structure is crucial to obtaining favorable recovery results. The reconstructed structures are often incorrect and not in accordance with human visual system characteristics if the damaged structures are connected simply based on distance. Thus, the method must search a similar structure to perform reconstruction by similarity matching.

2.2.1. Damaged structure pairing

To obtain relatively reliable reconstructed structure and restoration results, similarity matching of the damaged structure is performed based on color and curvature. Two similar damaged structures are paired and connected by the reconstruction process. First, a feature patch \( C_{L_i} \) of a broken structure \( L_i \) is selected based on following three conditions: (1) A 41 × 41 pixel patch exists within a known part of the image; (2) The center point of the patch is located on \( L_i \); (3) The center point of the patch is the nearest one to the corresponding T-junction point. Then, the color similarity is measured between the feature patches:

\[
S_1(L_i, L_j) = \text{SSD}(C_{L_i}, C_{L_j})
\]

where \( \text{SSD} \) means the sum of squared differences. The curvature similarity of the two broken structures is defined as:

\[
S_2(L_i, L_j) = \left| \text{cur}_{L_i} - \text{cur}_{L_j} \right|
\]

where \( \text{cur}_{L_k} \) is the curvature of \( L_k \) (\( k = i,j \)).

Based on the color information and curvature feature, the matching measurement between damaged structures \( L_i \) and \( L_j \) is defined as:

\[
M(L_i, L_j) = \arg \min_{i,j\in\{1,\ldots,N\}} \{ \alpha \cdot S_1(L_i, L_j) + \beta \cdot S_2(L_i, L_j) \}
\]

where \( N \) is the total number of missing structures, and \( \alpha \) and \( \beta \) are coefficients of weight. \( S_1(L_i, L_j) \) describe the color distribution similarity around the missing region. Moreover, \( S_2(L_i, L_j) \) reflects the degree to which the broken structures have a similar trend. Both color and curvature of the structure are important clues for structure matching. Here, \( \alpha \) and \( \beta \) are set to 0.8 and 0.2, respectively, based on an experiment.

2.2.2. Damaged structure reconstruction

The damaged structure can be reconstructed after being grouped into pairs. The structure reconstruction involves connecting the two broken line sections into an integrated whole to conform to human visual perception. The missing structures that are paired are firstly constructed. Then, for other missing structures that are not successfully matched, they are extended based on their own curvature until being connected to a known region or other reconstructed structure. There are five broken structures in Fig. 2(d), where \( \{L_3, L_4\} \) and \( \{L_1, L_3\} \) are matched pairs, and \( L_2 \) is left alone.

We chose the Euler spiral to reconstruct the broken structure to enable good scale invariance. The formula of the Euler spiral is defined as [26]:
\[
C(s) = \begin{cases}
    C_0 + e^{\gamma s} s; & \gamma = 0, \ k_0 = 0 \\
    C_0 + \frac{e^{\gamma s}}{k_0} (\sin(k_0 s) + i(1 - \cos(k_0 s)))); & \gamma = 0, \ k_0 \neq 0 \\
    \frac{\pi}{\sqrt{|\gamma|}} \times (\text{sign}(\gamma))(L(s)(\frac{k_0 + \gamma s}{\sqrt{\pi |\gamma|}}) - L(s)(\frac{k_0}{\sqrt{\pi |\gamma|}})) & \gamma \neq 0 \\
    + i(S(s)(\frac{k_0 + \gamma s}{\sqrt{\pi |\gamma|}}) - S(s)(\frac{k_0}{\sqrt{\pi |\gamma|}})) & \gamma \neq 0
\end{cases}
\]

where \(C_0\) is a point on the Euler spiral. The tangential angle, initial curvature, and changing ratio of the curvature at this point are \(\theta_0, \ k_0\) and \(\gamma\), respectively. Moreover, \(s\) denotes the arc length, and the function of the tangential angle is:

\[
\theta(s) = \frac{1}{2} \gamma s^2 + k_0 s + \theta_0
\]

\(C(s)\) and \(S(s)\) are the Fresnel integration:

\[
L(s) = \int_0^s \cos\left(\frac{\pi}{2} \xi^2\right) d\xi, \quad S(s) = \int_0^s \sin\left(\frac{\pi}{2} \xi^2\right) d\xi
\]

Construction of a curve with minimal energy that can connect broken structures \([25]\) can satisfy human visual perception. That is, the Euler spiral connecting broken structures should satisfy the following energy function:

\[
E_k = \int_0^L k_s^2 ds \quad s \in [0, L]
\]

where \(k_s = dk(s)/ds\) is the curvature change function, \(k(s) = \gamma s + k_0\) is the curvature formula, \(\gamma\) is the curvature change ratio, \(k_0\) denotes the original curvature, and \(L\) is the arc length.

Considering the difference between damaged structures, the edge structure and corner structure are respectively reconstructed. The straight line and curve are reconstructed using the Euler spiral. Two extended Euler Spirals are used to reconstruct missed corner structure because the interpolated Euler spiral between any two points on Euler spiral is similar, which means Euler spiral is extensible and can maintain the continuity between two separate segments very well \([26]\). When a part of image is missed, it is hard to judge automatically that it is edge structure or corner structure based on the state-of-the-art technology, so the missed structure types will be given interactively. The reconstructed structures of mountain and ancient drinking vessel in Fig. 2 are shown in Fig. 3. It can be observed that the structures are perfectly preserved.
3. Filling in Texture under the Reconstructed-Structure Constraint

The repair order is critical for exemplar-based image inpainting methods. The priority is determined mainly by two factors: the confidence term and the data term. The confidence term denotes the ratio of known information within the target patch. The data term describes the intensity of the structure information. However, the data term can merely denote the structure intensity information of a single pixel for the traditional exemplar-based priority. The optimum repair order cannot be obtained usually for the weakness of describing the structure information of the whole patch. In this paper, the texture is filled in under the constraint of the reconstructed structures.

The reconstructed structures are used as a constraint term of the structure intensity information, which can guarantee that the part with a salient structure can be preferentially repaired. The number of pixels located in the structure is tallied and used as a component of the priority. Thus, the improved exemplar-based image inpainting priority combined with the reconstructed structure is defined as:

\[ P(p) = C(p) \cdot (D(p) + S(p)) \quad (10) \]

\[ C(p) = \sum_{q \in \Omega_{\Psi_p}} \left[ \frac{C(q)}{\left| \Psi_q \right|} \right] \quad (11) \]

\[ S(p) = \sum_{q \in L'} \left[ \frac{S(q)}{\left| \Psi_p \right|} \right], \quad S(q) = \begin{cases} 1, & q \in L' \\ 0, & \text{otherwise} \end{cases} \quad (12) \]

where \( C(p) \) is the confidence term, which means the ratio of known pixels in target patch \( \Psi_p \). \( \left| \Psi_p \right| \) denotes the area of \( \Psi_p \). \( D(p) \) is the data term, which means the isophote of pixel point \( p \). \( S(p) \) is the ratio of reconstructed structure \( L' \) within the target patch, and it denotes the restraining strength of the structure. Furthermore, \( q \) is the pixel located in reconstructed structure \( L' \). The patch close to the margin of the target region and having a center point located on the structure is preferentially repaired. During the repair process, the undamaged region containing the known structure that connects to the reconstructed structure is selected as the source region to guide and restrain the texture recovery.

As shown in Fig. 4(a) and Fig. 4(c), for reconstructed structure \( L_1' \), the undamaged region containing known structure \( L_1 \) is selected as the source region. Similarly, reconstructed structure \( L_2' \) and \( L_3' \) can also obtain their own respective source regions. The texture filling-in results under the constraint of reconstructed structures and source regions are shown in Fig. 4(b) and Fig. 4(d), respectively.

The texture repair for patches that contain the reconstructed structure is very fast because the searching process of matching the patch is under the constraint of the source region and the connected known structure. For other patches, the matching patches are searched within a \( 60 \times 60 \) neighbor region of the target patch. Global searching will be employed only when the similarity is less than 75%. This searching strategy can notably reduce the searching time and simultaneously guarantee the repair performance.

4. Experimental Results and Analysis
The computer environment of our experiment included an Intel 2.66 GHz CPU with 4.0 GB of memory. Programming was executed using MATLAB 2012a. The patch size was $9 \times 9$. To validate the efficiency of the proposed algorithm, experiments for different types of images were performed. The experiments were divided into two groups: one restored the image damage and another repaired a removed object. The peak signal-to-noise ratio (PSNR) and mean squared error (MSE) were used as the objective evaluation criteria for the damaged-image repair experiments. Human subjective opinions were also combined to measure the repair quality. For the object removal experiments, only the subjective standard of human visual perception was compared because no ground truth image was available. The required time was used as the measuring standard of the repair efficiency for both types of experiments.

![Repair results under the constraint of reconstructed structures.](image1)

4.1. Experiment of Image Damage Repair

Three experiments were performed for image damage repair, as shown in Fig. 5 to Fig. 7. Fig. 5(a) and Fig. 7(a) are natural images and Fig. 6(a) is a picture of a Shang Dynasty bronze cooking tripod from a museum. The white regions are man-made damage targets that require repaired. Fig. 5(c) shows the edge structure reconstructed by the Euler spiral. Fig. 6(c) and Fig. 7(c) are corner structures reconstructed using extended Euler spirals. Fig. 5(d), Fig. 6(d) and Fig. 7(d) are image repair results of the proposed image completion method based on structure reconstruction and constraint (SRC). Fig. 5(e), Fig. 6(e) and Fig. 7(e) are results of content-aware fill [23]. Fig. 5(f), Fig. 6(f) and Fig. 7(f) show...
repair results of Criminisi [6].

It can be observed from Fig. 5(d) that the damaged region is restored well by the constraint of the reconstructed edge structure. In Fig. 5(e), the structure for the results of content-aware fill is inconsistent and the texture is incoherent with its neighbor. The repair result of Criminisi in Fig. 5(f) is texture-coherent with its neighbor; however, a small part of the structure is also inconsistent. This is because Criminisi does not consider the image structure and the order of repair is at times unreasonable.

In Fig. 6(d), the repair effect of structure and texture are satisfied because the proposed method reconstructs the damaged corner structure first and then fills in the texture under the constraint of the reconstructed structure. The result of content-aware fill in Fig. 6(e) has some bulging parts for the structure, and the texture is blurred. This is because there is no similar region with a target region in the original image and no corresponding structure can be found when searching the matching patch. The repair result of Criminisi in Fig. 6(f) fails because the structure is broken and the texture is incoherent.

The recovery result of the proposed method in Fig. 7(d) shows good preservation of structure consistency, and it satisfies human visual perception. The texture is coherent with its neighbor. Fig. 7(e) is the repair result of Content-Aware Fill, it can be observed that error texture is filled in. For the result of Criminisi in Fig. 7(f), the texture is incoherent with neighbor and is unable to satisfy human visual perception.

The objective evaluation criteria of damaged image repair are shown in Table 1. It can be observed that the PSNR values of proposed method increase 3.43~12.85dB than content-aware fill and Criminisi. The MSE values of the proposed method are much lower than those of the other two methods. That is because the proposed method reconstructs the structure first, and then fills in the texture under the constraint of the reconstructed restructure. This strategy can preserve the structure consistency well and obtain better results.

The time consumption of our method was compared with that of the Criminisi method, as shown in Table 2. Although the proposed method must segment and reconstruct the structure, the time of filling in the texture is reduced by the constraint under the reconstructed structure. That is, the global searching is avoided, and the total time consumption is slightly higher than that of Criminisi. It is within an acceptable level.

4.2. Experiment of Object Removal

The results of object removal are shown in Fig. 8 to Fig. 10, where Fig. 8(a), Fig. 9(a) and Fig. 10(a) are target images (the red regions are target regions to be repaired). Fig. 8(b), Fig. 9(b) and Fig. 10(b) are results of structure reconstruction of the proposed method. Fig. 8(c), Fig. 9(c) and Fig. 10(c) are the repair results of the proposed structure reconstruction and the constraint based method.
Fig. 5. Repair results of “nursery garden.”

Fig. 6. Repair results of “Shang Dynasty bronze cooking tripod.”
The result of the “small house” removal experiment of the shift-map method [15] is shown in Fig. 8(d). The texture of cloud is filled into the region of the sea because shift-map ignores coherency between neighborhoods during pixels rearrangement. The results of the proposed method, content-aware fill, and the He method [17] have good performance on structure consistency and texture coherency.

In Fig. 9(d), “traveller” is removed with the shift-map method. Similar to Fig. 8(d), the texture of soil is filled into the region of the stone wall. For the repair result of content-aware fill in Fig. 9(e), the texture within the stone wall region is blurred and the area within the soil is incoherent with the neighborhood. The result of He in Fig. 9(f) is relatively better, however. The arc structure in the soil region is inconsistent because the dominant offset that reflects the structure is difficult to be calculated for images with low structure repetition and images with curving structures. The proposed method repairs images based on structure reconstruction and constraints. First, straight lines and curve lines are reconstructed using the Euler spiral, which can guarantee the consistency of the
structure. Filling in texture under the constraint of the reconstructed structure can maintain the texture coherency well. Compared with other methods, the results of the proposed method preserve the structure of stone wall and curves in soil well. The texture is clear and coherent with the neighbor, and the repair performance satisfies human visual perception.

A “kid” object must be removed in Fig. 10. The result of shift-map in Fig. 10(d) cannot preserve the structure well. Fig. 10(e) is the result of content-aware fill, the lines of steps are missed or bulged. The result of He is shown in Fig. 10(f), where the edge of side slope is broken. By contrast, the result of proposed method is more natural in structure and texture. The time consumption was compared in Table 3. It can be observed that the proposed method is faster than shift-map algorithm. It also has better structure consistency and texture coherence as mentioned before; thus, it has better performance than the other methods.

From the repair results of image damage and object removal, the proposed method based on structure reconstruction and constraint can preserve the image structure well. The texture filling-in process under the constraint of the reconstructed structure is natural and coherent. The quality of the repaired images is better than that of the other methods and the results conform to human visual perception.

![Fig. 8. Results of removing a "small house" object](image-url)
5. Conclusion

An image inpainting algorithm was proposed in this paper. First, the damaged structures of target image are detected to obtain the location of missed structures. Then, the damaged structures are paired up and reconstructed based on their features. Finally, the texture is filled in under the constraint of reconstructed structures. The algorithm detects T-junctions based on segmentation result of target image, thus, the broken points of missed structure can be located automatically. The broken points of missed structure are paired up based on the color and curvature information. The missed edge structure is reconstructed by Euler spiral which satisfies energy minimization and corner structure is reconstructed using intersection of two extended Euler spirals.

The above approach provides a solution to the problem of the corner structure being unable to repaired for current image inpainting methods. The experimental results show that the proposed method performed well when repairing small regional damage, such as straight-line and curve damage. The proposed method also out-performed the other methods in the large region of object removal. The results preserved the edge structure and texture consistency perfectly and satisfied human visual perception as well. It can be applied to the recovery of natural scene and cultural relic pictures.
Table 3. Comparison of Consumed Time for the Object Removal Experiment

<table>
<thead>
<tr>
<th>Image size</th>
<th>Area ratio of damage (%)</th>
<th>Time consumed (s)</th>
<th>Shift-map [15]</th>
<th>Proposed SRC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig. 8</td>
<td>265×400</td>
<td>21.63</td>
<td>47.62</td>
<td>31.03</td>
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<tr>
<td>Fig. 9</td>
<td>380×214</td>
<td>12.71</td>
<td>52.48</td>
<td>35.36</td>
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<tr>
<td>Fig. 10</td>
<td>375×500</td>
<td>16.93</td>
<td>56.91</td>
<td>39.15</td>
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</tbody>
</table>

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