

# An Image Inpainting Technique on Chinese Paintings

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**Abstract.** With the popularity of Chinese culture, traditional Chinese artworks become more valued than before. Though many precious artworks have been luckily preserved, some damages on them cannot be easily fixed physically. To effectively document those valuable artworks, scholars and collectors have been using scientific methods to conserve them digitally. This paper proposed a two-layer digital image inpainting technology that offers an automatic restoration and completion for damaged Chinese paintings. This algorithm is composed of two layers: the skeleton layer and the texture layer. In the skeleton layer, a skeleton inpainting algorithm is proposed to produce the skeleton distribution of the missing region. In the texture layer, we restore the content of the missing region using the neighboring area together with the skeleton distribution. Experimental results demonstrate that the proposed method performs well under different conditions.

**Keywords:** Chinese paintings, edge detection, exemplar-based image inpainting, image completion, skeleton inpainting

## 1 Introduction

Chinese painting is one of the oldest artistic traditions in the world. Many precious paintings have been luckily preserved after a long history; however, the marks left on them by age or wars are not easily removed. To effectively document those valuable images, scholars and collectors used scientific methods to conserve them digitally. Image completion is one of the techniques to restore the image of the damaged paintings. Efros and Leung [1] and Drori et al. [2] adopted texture synthesis algorithms to perform the inpainting process. Some algorithms [3-5] can work well if the damaged region is of small size, like smudges and creases. However, if the size of missing or damaged region is too large, these approaches would lead to a fuzzy result.

There are two common types of image completion technology: texture synthesis and image inpainting. For texture synthesis, it relies on analysis variations and conditions to search for a texture sample from the image input to complete the assigned damage region. It is capable of filling in a region with a texture structure that has consistency and regularity. Image inpainting techniques extract the reliable information by using the surrounding area of the target region and then fill in the damaged area using algorithms such as partial differentiation or interpolation. This approach is suitable for a small region. More recently, various studies with innovative ideas for image inpainting have been improved to fill in a larger damaged area.

There are different approaches for texture synthesis. Heeger and Bergen [6] synthesized a suitable texture image by using parametric models. It establishes histograms of the sample texture together with the noise, collapses the noise pyramids matching to the histogram, and gets the synthesis result. A non-parametric type approach regenerates the sample skeleton of the image, which is referred to the pixel-based texture synthesis. As shown in [1], it arranges some initial points in the image that is to be synthesized and then searches for some matching points in the sample image through the size-adjustable neighborhood. Finally, it randomly picks up one of those qualified matching points to fill in the

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synthesized image. High-quality results can be obtained by using this method for artificial or natural texture synthesis; however, the computation cost is high. Considering the computation cost, Liang et al. [7] proposed a patch-based method, which searches the best-matched patch from the input texture and repeats the inpainting process for the new texture. By doing so, it can effectively reduce the computation time.

Bertalmio et al. [4] proposed the first aspects of inpainting which adopts a scheme based on the partial differential equation. It defines the range, the contour, and image information of the target. The partial differential equation is used to compute the gradient vector outside the target range by tracing the contour. Afterward, it uses isophotes to find the direction for the minimum spatial change. The image information outside the target range is transmitted to the inside for maintaining continuity of the linear skeleton. Based on the concepts of [4], Oliveria et al. [8] proposed an improved version, which can not only reduce the time required for image inpainting but also provide a better result. These approaches are suitable for the small damaged areas such as cracks or scratches.

The acquired image can be treated as the composition of texture as well as a skeleton. Therefore image inpainting can be implemented by combining the texture synthesis with the partial differential equation [9-10]. The key of the approach is to decompose an image into two parts: the texture and the skeleton, and it is followed by using texture synthesis and the partial differential equation for the image inpainting. Criminisi et al. [11] proposed an exemplar-based method in which the order of inpainting was determined by the gradient variation of the target area, and therefore not only the computation time was reduced significantly but also the linear skeleton part for the inpainting was prioritized. Sun et al. [12] proposed a process for image inpainting by extending the image skeleton. It extends the known skeletons into the target region manually, and then uses tensor-voting algorithm to find out the most similar image for the filling area. Rares et al. [13] used the curvature of contours around the target region as the feature which is used to partition the target region. After the partitioning process, the work executed the inpainting process in those regions of the same segment. This method can automatically complete all the image segments within the target region; however, it is not suitable when the image structure is complicated. Chang and Hsu [14] proposed an improved version of the exemplar-based method which takes into account the edge points to improve the accuracy of the confidence value. Moreover, the searching range is designed to adaptive to the size of the missing area, so the completed results are also improved.

Due to the effectivity of deep neural networks (DNN), some works adopt the technology to solve inpainting problems. These works consider inpainting problems from two aspects: structured prediction [15-16] and image generation [17-18]. Structured prediction problems can be formulated as energy minimization of a network. It models the structural relationship among local regions of the input image and estimates pixel intensities of the missing regions. Yang et al. [15] proposed a multi-scale neural patch synthesis method optimizing both the missing content and texture of an input image through two networks. The content network is used to infer the missing data and generate an image, and the texture network enhances the texture of the image. For image generation problems, Generative Adversarial Networks (GAN) [19] is a popular method. Pathak et al. [17] proposed a network combining GAN and encoder-decoder network. The network is trained by minimizing the combination of reconstruction loss and adversarial loss. Yeh et al. [18] proposed a manifold search method for image inpainting based on a Deep Convolutional Generative Adversarial Network (DCGAN) [20] with the combination of contextual loss and perceptual loss. The contextual loss is designed with the hypothesis that the importance of an uncorrupted pixel is highly related to the near corrupted pixels, while the perceptual loss is same as the adversarial loss in DCGAN [20] that ensures a perceptually realistic output image.

The rest of this paper is organized as follows. Section 2 explains the composition and patterns of Chinese paintings. Section 3 details the skeleton layer inpainting method, and Section 4 details the texture layer inpainting method. Section 5 gives the experimental results and discussion. Finally, conclusion and future works are drawn in Section 6.

## 2 Image Inpainting for Chinese Paintings

### 2.1 Chinese Paintings and Related Inpainting Methods

Chinese painting is a typical traditional painting from China with a long history. It was originated from the Chin-Han Dynasty and reached the peak during Tang-Song Dynasty. Landscapes, flowers and birds, and portraits in Chinese paintings are composed by using calligraphy and ink to sketch the lines and brush the area with various ink tonality. Techniques for Chinese paintings are a combination of brush and ink works. The brush work refers to those points, lines, and planes in the painting. It has been summarized into five kinds of brush works including centered, sided, exposed, reversed, and concealed. The ink work is referred to the varying ink density on the painting, and there are five inks and six colors. The five inks contain dense, diluted, dry, wet and black. If an image presents the scene from a far distance or some protruding area, they are expressed in the diluted ink; if an image presents the scene from a short distance or something hollow, they are expressed in the dense ink. A dry brush is to express withered branches in the painting, whereas a wet brush is to express budding trees in greens. The six colors are black, white, dry, wet, dense and diluted, and they are used to express a complicated color variation.

Pei et al. [21] used color space conversion and adjustment of color contrast to make those aged and fuzzy images clearer. As for the damaged part, inpainting is first operated for the lines of the image manually. Then with the texture synthesis method of Markov Random Field, inpainting is executed for all the damaged regions. Shih and Chang [22-23] proposed the methods which are derived from patterns of Chinese paintings. The most diluted color is used for the background whereas denser colors are used for expressing the front scenery. The work uses the K-mean classification algorithm to separate the major color region from other color regions. That is, the more concentrated colors are used for the front scenery, and the skeleton of the real object will be separated from those diluted colors used for the background or the smudging and stained areas. After this process, inpainting is executed separately on the target region at these two image layers, and then these inpainted results are merged to bring final result. Pei et al. [21] used the approach of texture synthesis for inpainting, which was effective for restoring a large range of image damage. However, it still requires manual operation. Therefore, this method cannot provide complete automatic inpainting. Shih's works [22-23] work well for a small damaged size since their methods are based on multiple-resolution approach. However, when it is applied for a region of larger size, it would result in a little-blurred outcome.

### 2.2 The Proposed Approach

To improve the correctness of image inpainting, this work separates the to-be-repaired region into two layers for the inpainting process: the skeleton layer and the texture layer. The skeleton layer is the black and white image derived from edge detection of the original image. This is acquired by using the edge image surrounding the target region to compute the skeleton distribution inside the target region. Based on the distribution result, one can either expand the inpainting range or partition the to-be inpainting region into smaller areas. In other words, if the contour of the target region is linked to the detected skeleton in the skeleton image, we perform inpainting process for skeleton image inside the target region and extend the skeleton of the object as an inpainting boundary for the texture layer. The texture layer is the image with the added skeleton constraints, and it uses the exemplar-based image inpainting for the target region. If the target region does not contain any skeleton distribution, then inpainting will be conducted directly in the texture layer. To achieve fast inpainting for a larger region, the work adopts an enhanced algorithm [14] by re-defining the searching range for the target region. It ensures that the source of the replication is selected from the nearby region. Fig. 1 shows the system overview.

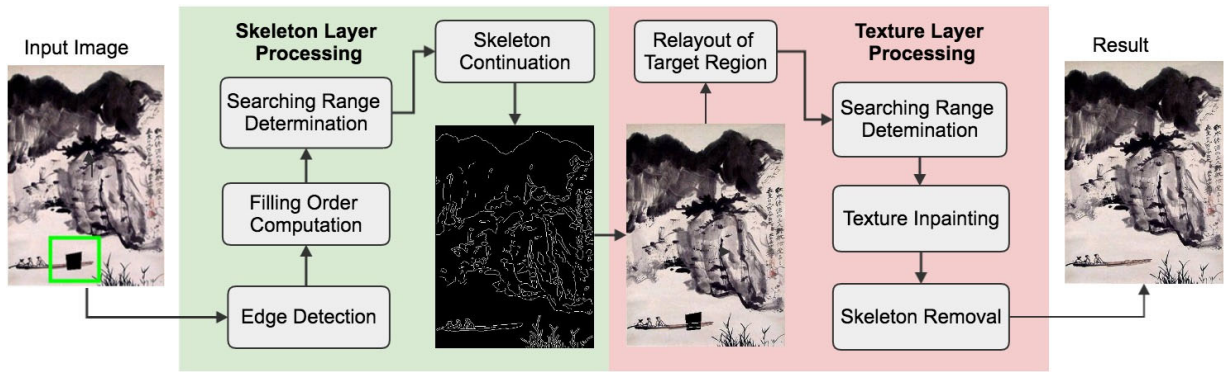


Fig. 1. System overview

### 3 Inpainting in Skeleton Layer

For inpainting of a large target range of Chinese paintings, some errors such as discontinuity of the object boundary or incorrect textures could happen due to the wrong prediction of the structure. To avoid those problems, we use edge detection to find the skeleton distribution around the target region. If a skeleton is found, it can be used to provide constraints for the inpainting.

The procedure in the skeleton layer contains four steps: (1) edge detection; (2) determination of the filling order; (3) finding of the searching region; (4) skeleton filling process. The related notations are shown in Fig. 2. The input image obtained from the edge detection is denoted as  $\mathbf{I}$ , the damaged area (target region) is denoted as  $\Omega$ , and the target contour is denoted as  $\partial\Omega$ . The entire image deducting the target region is defined as the source region.

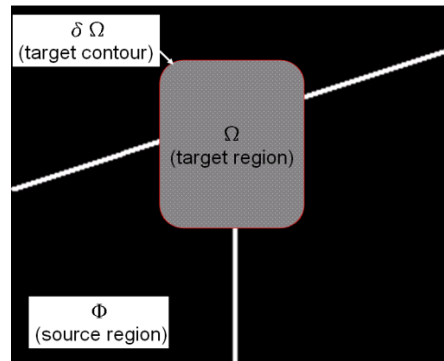


Fig. 2. Notations

#### 3.1 Edge Detection

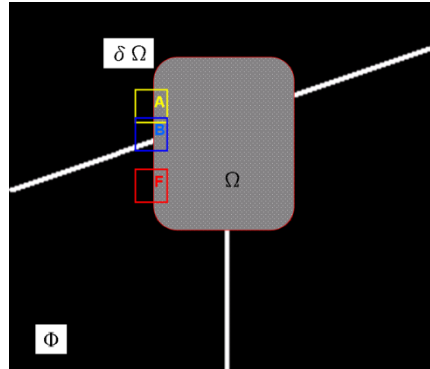
To obtain the object skeleton in the Chinese paintings, the system uses the Canny edge detection to extract image patterns. The steps are described as follows.

- (1) Use Gauss Function  $G(i, j)$  to convolute the original image  $B(i, j)$ .
- (2) Obtain the gradient map for  $S(i, j)$  and carry out the thinning process.
- (3) Use the high threshold value  $e_h$  for noise filtering and find a boundary of a stronger contrast.
- (4) Using the low threshold value  $e_l$  to detect a boundary of a weaker contrast, and then connect all the major boundaries of each section to obtain the image pattern.

#### 3.2 Determination of Filling Order

After completing Canny edge detection, we use the acquired edge map to search for skeleton information in the target region. The first step is to give a series of patches to every point along the

contour of the target region. This is shown in Fig. 3.



**Fig. 3.** Determination of filling order

The central points of these patches are all located on the contour of the target region, and the next step is to find out a patch with the highest structure priority. The definition of structure priority is defined as follows:

$$SP(p) = \alpha C(p) + \beta ER(p) \quad (1)$$

Where  $\alpha$  and  $\beta$  are the weighting factors;  $C(p)$  is the confidence defined as the ratio of patch pixels that belong to the target region. If the confidence value is high, the lesser the pixels are needed to be filled. The confidence value is defined in Eq. (2).

$$C(p) = \frac{\sum_{q \in \Psi_p \cap (I-\Omega)} C(q)}{|\Psi_p|} \quad (2)$$

$$C(q) = \begin{cases} 1 & \text{if } q \in \text{target region} \\ 0 & \text{otherwise} \end{cases}, \text{ and } |\Psi_p| \text{ is the patch size} \quad (3)$$

If pixel  $q$  of patch  $p$  belongs to the target region  $\Phi$ , then  $C(q) = 1$ ; else if it does not, then  $C(q) = 0$ . The confidence value  $C(p)$  of patch  $p$  is acquired by summing up all the confidence values within patch  $p$  and then normalized by the patch size  $|\Psi_p|$ .

$ER(p)$  is the edge ratio for computing the skeleton strength of patch  $p$ . If pixel  $q$  is an edge point, then  $e(q) = 1$ ; else if it is not, then  $e(q) = 0$ . When the proportion of the edge points of a patch is larger, the priority of inpainting is higher. The definition of  $ER(p)$  is defined as follows.

$$ER(p) = \frac{\sum_{q \in \Psi_p \cap (I-\Omega)} e(q)}{\sum_{q \in \Psi_p \cap (I-\Omega)} C(q)} \quad (4)$$

$$e(q) = \begin{cases} 1 & \text{if } q \in \text{edge} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

### 3.3 Determination of a Searching Region

In addition to the searching order, the searching region also affects the accuracy and speed of inpainting process. Generally speaking, the easiest way is to search the entire image; however, full searching would cost a longer computation time. According to the features of Chinese paintings, images from different regions indicate that the objects are of different distance and levels, and their techniques related to brush and ink works can also vary significantly. As a result, if the searching range of the target region is not

restricted, it is more than likely to cause an incorrect inpainting result. To solve this problem, this study uses Minimum Boundary Rectangle (MBR) [14] to set a unified boundary for the irregular contour of the target region, and the best effect is statistically calculated. The search region is the expansion of MBR, and the most suitable patch can be found in a reasonable range. It also reduces the required time for inpainting. Fig. 4(a) is the skeleton image; the red color rectangle in Fig. 4(b) is the MBR, and the blue color rectangle in Fig. 4 (c) is the searching range.

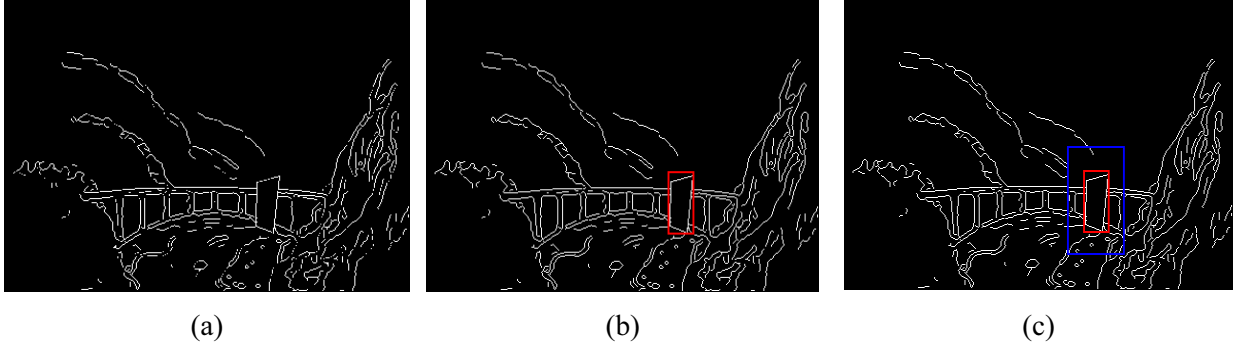


Fig. 4. Determination of the searching range

### 3.4 Skeleton Continuation

After computing the priority for all the patches along the contour of the target region, we select the patch  $\Psi_{\hat{p}}$  with the highest priority and look for the most matched patch  $\Psi_{\hat{q}}$  from the restricted searching range. The matching equation is described as follows:

$$\Psi_{\hat{q}} = \arg \min_{\Psi_q \in \Phi} d(\Psi_{\hat{p}}, \Psi_q) \quad (6)$$

Where  $d(\Psi_{\hat{p}}, \Psi_q)$  is the difference between  $\Psi_{\hat{p}}$  and  $\Psi_q$  and the sum of squared differences (SSD) is used to calculate the difference. The most similar patch  $\Psi_{\hat{q}}$  is used to fill in the blank space and complete the inpainting. Fig. 5 shows the filling process.

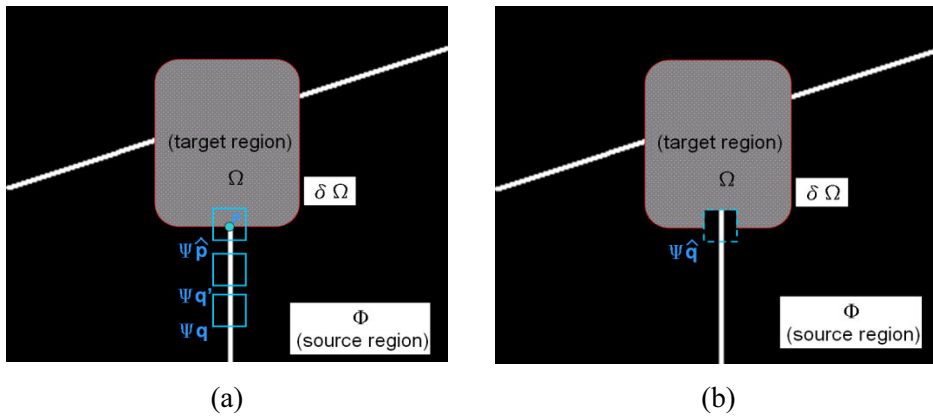


Fig. 5. Filling in process

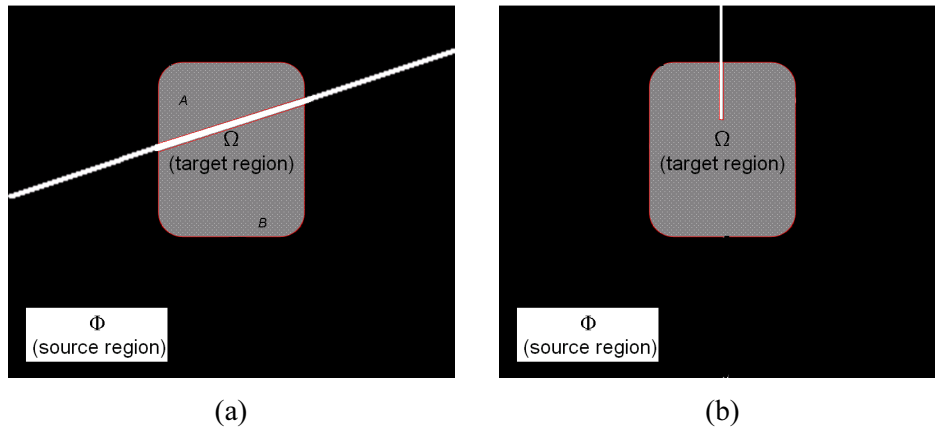
## 4 Inpainting in Texture Layer

To incorporate features of Chinese painting into the paper, the study has specifically added in a skeleton factor such that constraints can be added to the target region according to the skeleton distribution before the inpainting. This procedure can improve the accuracy of image inpainting. The main axis for

inpainting in this step is selected from [11], but similar to the approach used for skeleton inpainting, the searching range is restricted to reduce the matching time and thus increase the efficiency of inpainting.

#### 4.1 Relay of the Target Region

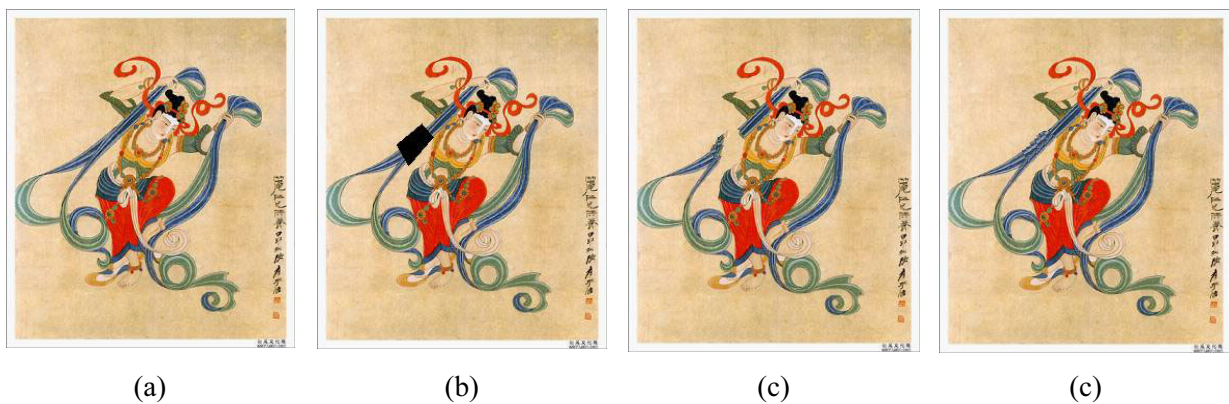
According to the result of skeleton inpainting, the restored skeleton is used in the target region and produces two types of modified target regions with different conditions. Fig. 6(a) shows that the target region is divided into two areas, A and B, by the new skeleton. The followed image inpainting of these two regions can be done separately. Fig. 6(b) shows the other case. Though the extended skeleton does not pass through the target region, it produces a modified target region with the newly added skeleton.



**Fig. 6.** Target region with a skeleton

#### 4.2 Determination of a Searching Region

Similar to the method used in the skeleton layer, the minimum boundary rectangle (MBR) is used to determine the range of the target region. The searching area is defined as the expansion of MBR. By adjusting the searching range, we can reduce the computation time significantly and improve the matching results. Fig. 7 shows an example. Fig. 7(a) is the original image; Fig. 7(b) is the image to be fixed; Fig. 7(c) is the inpainting result using the entire image as the searching range; Fig. 7(d) is the result of our proposed approach. It is observed that the inpainting result is shown in Fig. 7(c) is not appropriate because wrong patches are selected. The filling content in Fig. 7(d) is proper and the computation time is reduced as well.



**Fig. 7.** Comparison between different searching ranges

Fig. 8 explains the case shown in Fig. 6(a). Assume that areas 1 and 3 are the objects in a painting that have a similar color, but different painting styles and area 2 is a different object and with a different color. In Fig. 8(b), the target region has been partitioned using the added skeleton such that when giving

inpainting to the region A, the MBR (the red rectangle) and the expanding outward searching range (the blue rectangle) are recalculated. By doing so, the image searching range for a similar image can be restricted within area 1(yellow) and 2(green), and therefore effectively reduce the use of information from area 3. The result from above reveals that a consistent inpainting image can be archived. In Fig. 8(c), when inpainting of region B is executing, the searching range (the blue rectangle) is recalculated because of the partition. Fig. 9 explains the case of Fig. 9(b). By using this extended skeleton, image inpainting can be done by tracing the added boundary to acquire a better inpainting result. Fig. 9(a) shows the selection of the target region and Fig. 9(b) is the target region with added inpainting skeleton.

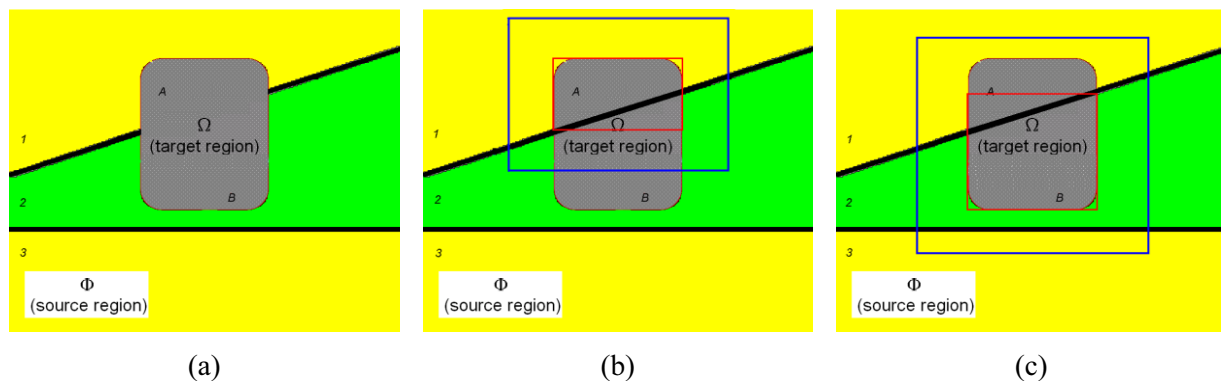


Fig. 8. The searching range of modified target region



Fig. 9. The painting with added inpainting boundary

### 4.3 Texture Inpainting

We adopt the inpainting method [11] to complete the modified target region. The corresponding notations are shown in Fig. 10.

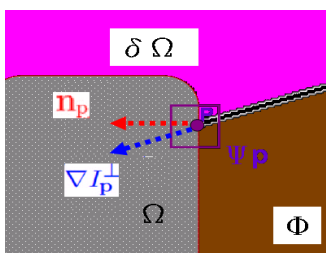


Fig. 10. Notations of [11]



As shown in Fig. 24, the input image is  $I$ , the target region is  $\Omega$ , the target contour is  $\partial\Omega$ , and the source region is  $\Phi$ . We compute the priority  $P(p)$  for each point at the contour of the target region which determines the inpainting order. The priority  $P(p)$  is defined as the product of the confidential value  $C(p)$  and the data term  $D(p)$ . The equations are shown as follow:

$$P(p) = C(p) \cdot D(p) \quad (7)$$

$$D(p) = \frac{|\nabla I_p^\perp \cdot n_p|}{\alpha} \quad (8)$$

Where the value  $\nabla I_p^\perp$  is the illumination direction of the point  $p$  in a 2D space and  $\alpha$  is the value used for normalization. After the priority computation, the next step is to carry out inpainting for the image. Eq. (6) can be used to find the best patch and get inpainting image.

#### 4.4 Skeleton Removal

The last step is to remove the added skeletons. We set the added skeletons as the new target region and fill them in the same inpainting process. Fig. 11 shows an example. Fig. 11(a) is the image with added skeletons. Fig. 11(b) is the inpainting result of the image with added skeletons. Fig. 11(c) is the final image after removing the skeletons.

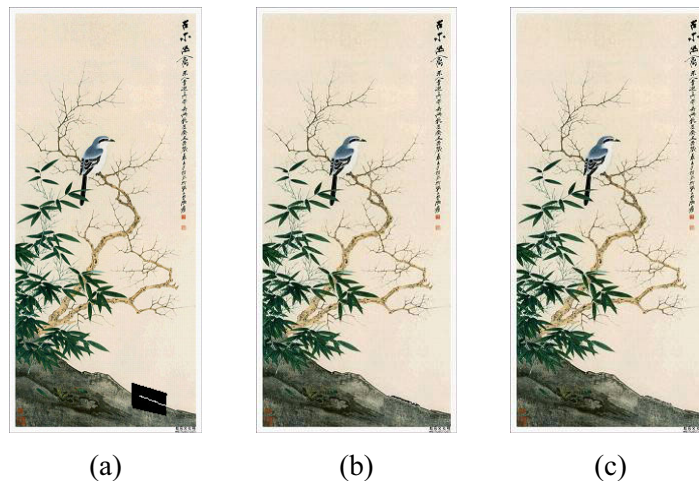


Fig. 11. Image inpainting with the removal of added skeletons

## 5 Experimental Results

In this section, we evaluate the proposed method by examining the inpainting results for different conditions and show the comparison among four methods.

Fig. 12(a) is the painting of birds. The area of two birds and tree branches located at the center of the painting is selected to be removed, as shown in Fig. 12(b). Fig. 12(c) shows the skeleton image after the process in skeleton layer. The inpainted skeletons are added into the target region to increase the boundaries for the inpainting, where the added skeletons of the tree branches do not pass through the target region, and there are no additional sub-regions. Fig. 12(d) shows the initial image in texture layer of which the target region contains the skeleton boundaries. The inpainting process can be operated along the added skeleton boundaries. Also, the filling-in process for the background also helps to avoid the possibility of crossing the boundaries. Fig. 12(e) is the inpainting result of the proposed method. The branches around the target region have been connected to form adjacent branches with any bird. Fig. 12(f) is the result of the method proposed by [11]. The branches are extended to the target region; however, the information is not strong enough to connect them. The reason is that there is no skeleton inside the target

region, so the inpainting can only rely on the priorities along the boundary of the target region. It is very possible to result in discontinuity in the restored image. Fig. 12(g) shows the result of the method proposed by [4]. Because it is more appropriate to the small target region, the result is fuzzy. Fig. 12(h) is the result using the software Teorex Inpaint.

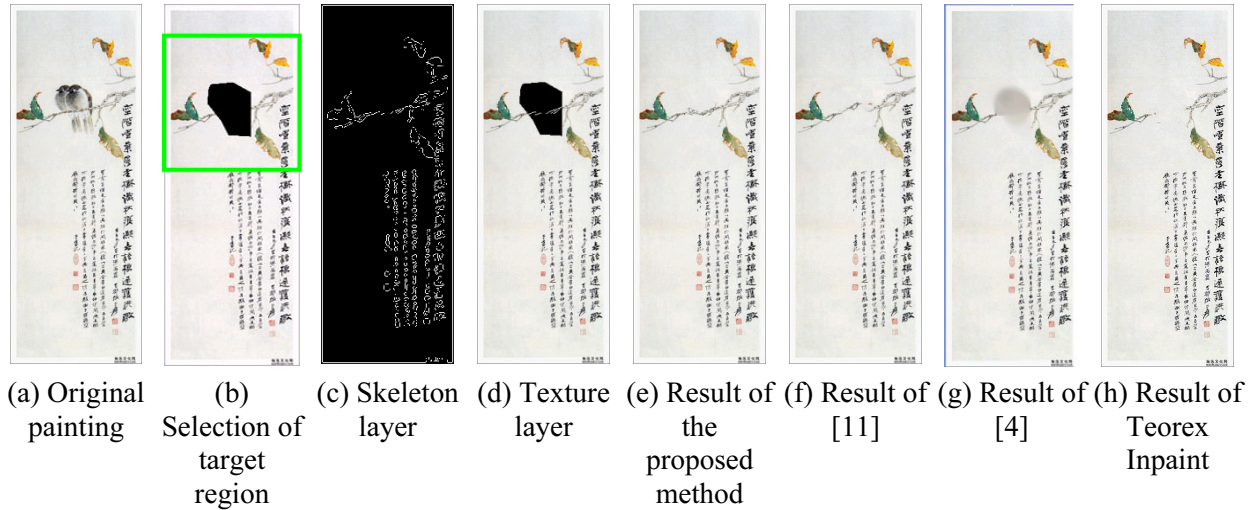


Fig. 12. Inpainting results

Fig. 13 shows a landscape painting and part of the boat is selected to be removed as shown in Fig. 13(b). Although the right part of the boat is removed, the boat shape can be restored after the processing in the skeleton layer (Fig. 13(c)). In this case, the target region is divided into three sub-regions as shown in Fig. 13(d) and followed the inpainting process for each one. Fig. 13(e) shows the inpainting result of our proposed method of which the boat is restored well. In Fig. 13(f), even though part of the boat has been extended, the restored boat is still incomplete. The boat is restored in Fig. 13(g) but the appearance is fuzzy. Fig. 13(h) is also a good result.

Fig. 14(a) shows a painting about a bridge among a mountain. The removed area is a part of the bridge as shown in Fig. 14 (b). Fig. 14(c) is the skeleton distribution in the skeleton layer and Fig. 14(d) is the texture layer. Fig. 14(e) shows the inpainting result of the proposed method. It is observed that the structure of the bridge is well-restored and some of the backgrounds are also appropriate. In Fig. 14(f), the lower part of the restored bridge is not completely recovered. The result in Fig. 14(g) is fuzzy since the size of the target region is too large. The upper part of the bridge is restored well in Fig. 14(h); however, the lower part is not covered by the background. Fig. 15 shows another example.

Fig. 16(a) is the original painting, and we select the area around the waterfall as the target region (Fig. 16(b)). Because of the strong edge features (Fig. 16(c)), the target region is divided into two areas by the long skeleton as shown in Fig. 16(d). Therefore, the boundary of the waterfall can be restored after the inpainting process of our proposed method (Fig. 16(e)). Due to lack of the skeleton information, the result in Fig. 16(f) has the different appearance. Fig. 16(g) produces a fuzzy result around the target region. The inpainting result of Fig. 16(h) is also good.

Fig. 17(a) is a landscape painting with a complicated background. Fig. 17(b) shows that some trees, as well as the neighboring background, are selected to be removed. Fig. 17(c) is the skeleton distribution in the skeleton layer of which contains many broken segments. Fig. 17(d) shows the image in the texture layer of which there is no long skeleton inside the target region. Fig. 17(e) is the inpainting result of our proposed approach; Fig. 17 (f), Fig. 17(g) and Fig. 17(h) are the results of the other methods. It can be observed that our result present a more nature scene than the others, especially for the appearance of trees.

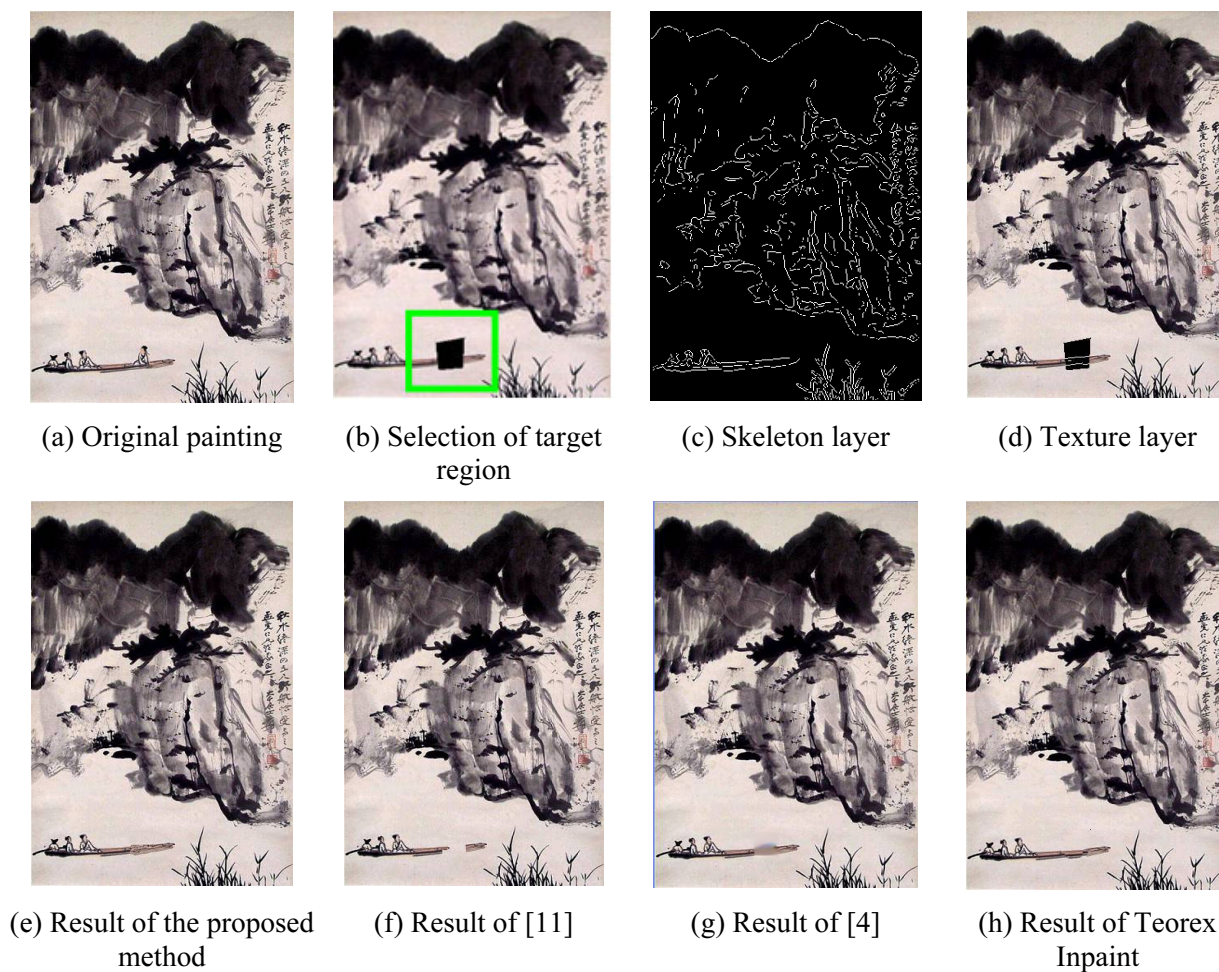


Fig. 13. Inpainting results

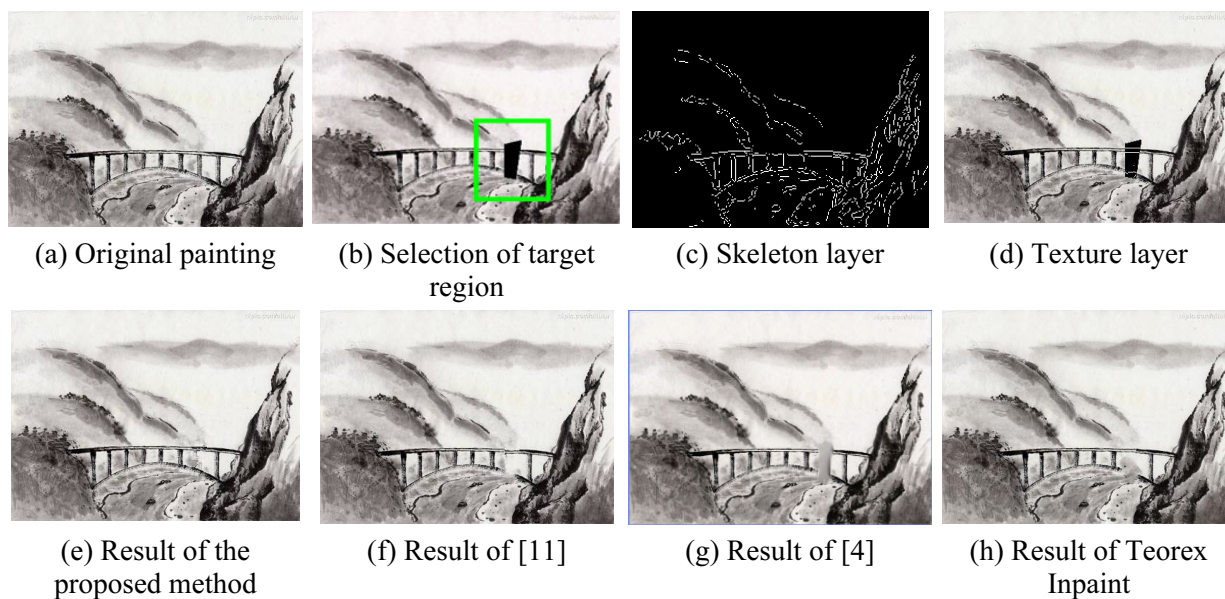
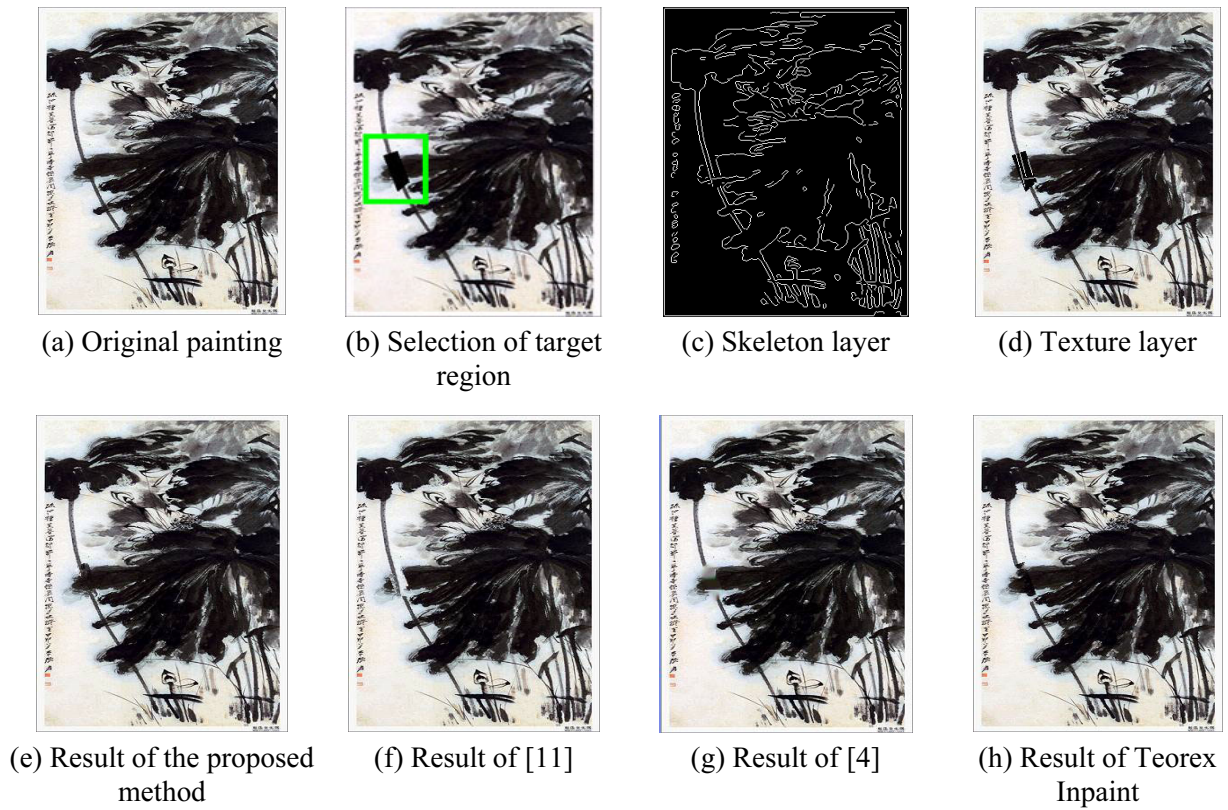
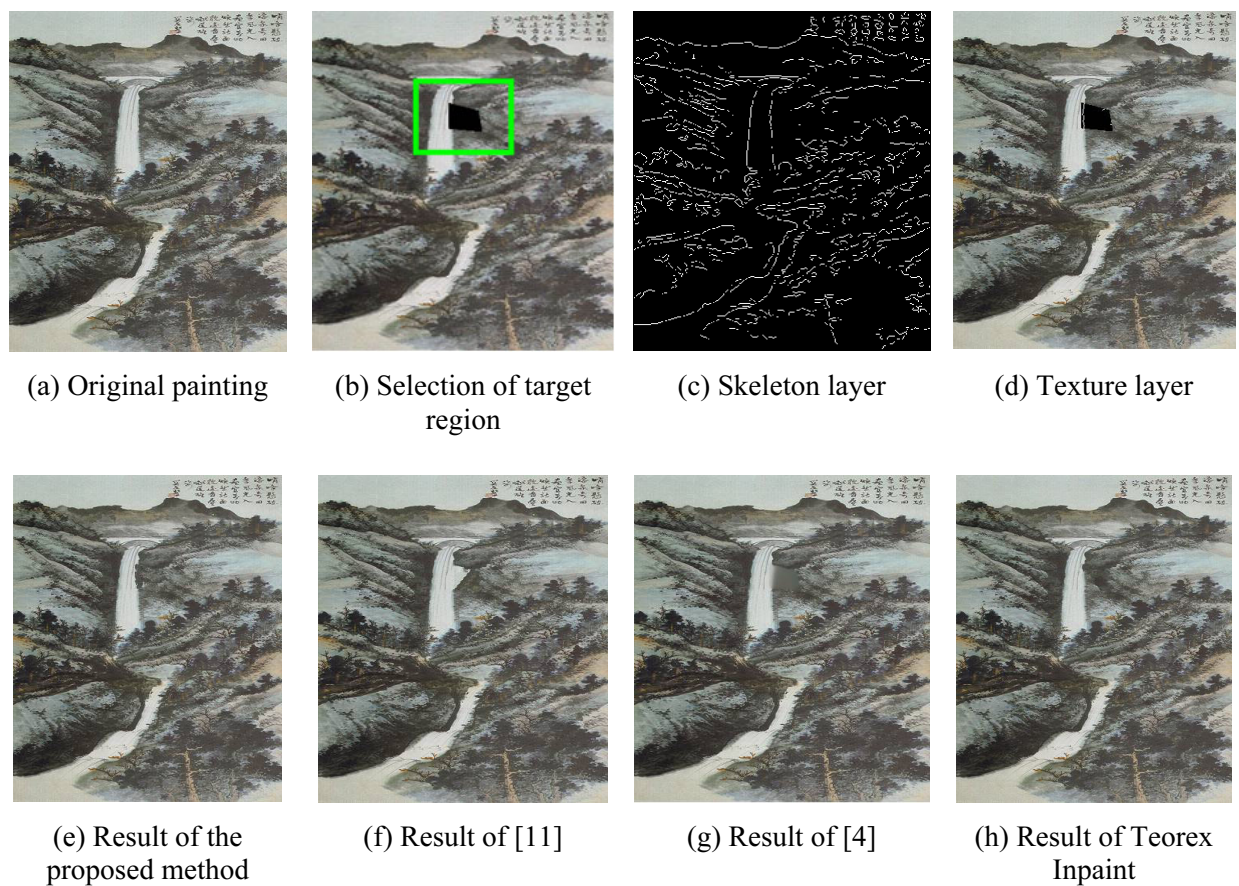


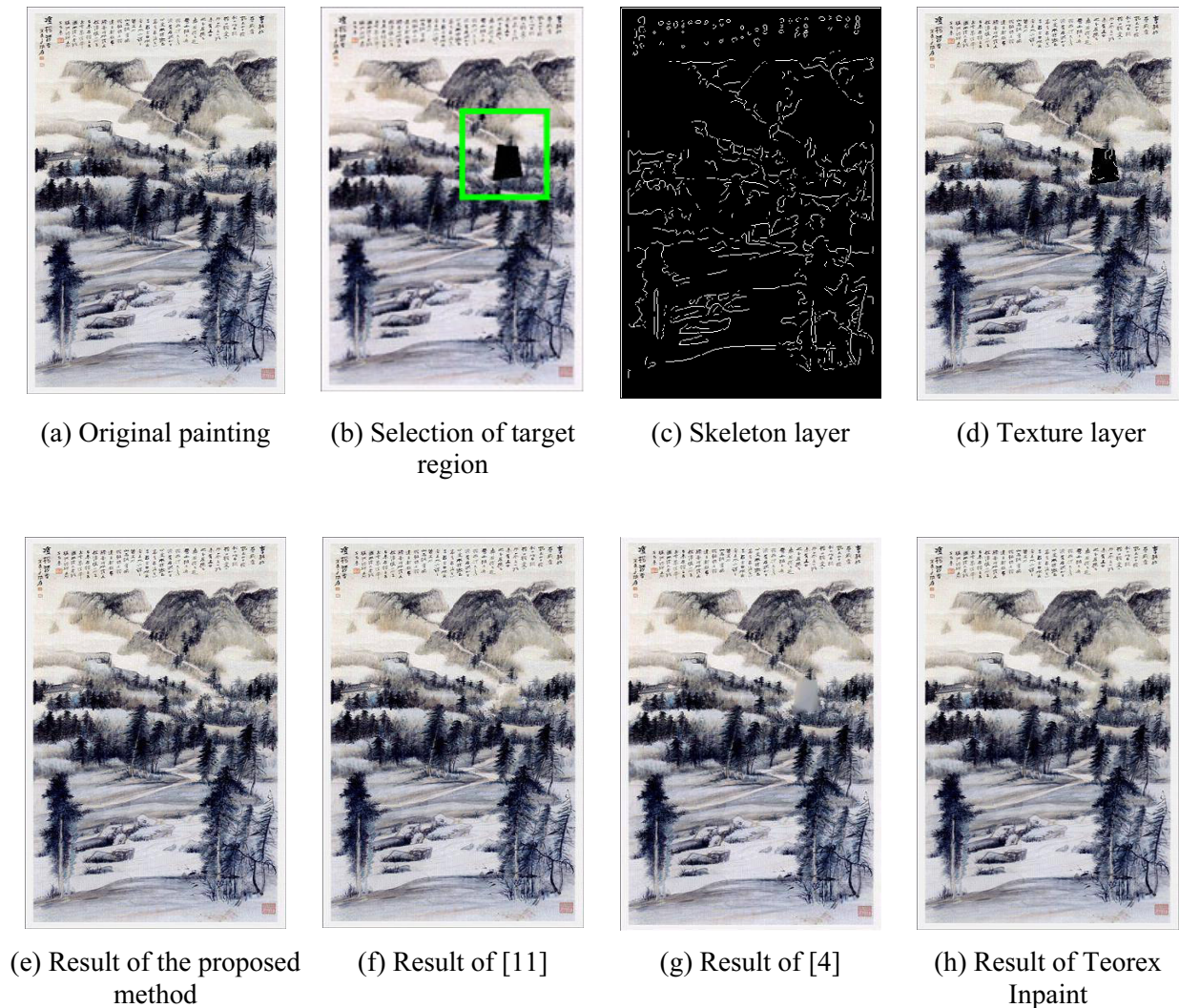
Fig. 14. Inpainting results



**Fig. 15.** Inpainting results



**Fig. 16.** Inpainting results



**Fig. 17.** Inpainting results

## 6 Conclusions

The paper presents a two-layer inpainting technique for Chinese paintings. A skeleton inpainting algorithm used in the skeleton layer is proposed to build up the skeleton distribution of the target region, which can help the inpainting process in the texture layer. Due to the additional skeleton information, the content inside the target region can be better restored. Moreover, the searching range is also determined according to the size of the target region. Compared with other methods, our approach has better performance of inpainting for Chinese paintings.

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