Image In-painting by Band Matching, Seamless Cloning and Area Sub-division

Subin Lee and Yongduek Seo

Sogang University, Seoul, Korea
{adrift, yndk}@sogang.ac.kr

Abstract. We propose a novel image in-painting method composed of two parts: band matching and seamless cloning. In band matching, a band enclosing the boundary of a missing region is compared to those from the other parts of the image. The inner area of the minimum difference band is then copied to the missing region. Even though this band matching results in successful in-painting in many practical applications, brightness discontinuity (a seam) may appear between the filled missing region and its neighborhood. We apply seamless-cloning to remove such discontinuity between the two regions. Examples show that this two step approach can provide a very fast and effective image in-painting. However, since this basic method using one patch may not deal with cases where there are abrupt changes of color or brightness along the boundary, we furthermore devise one more step: target sub-division. The target area is subdivided into small sub-areas, and the band matching and seamless cloning is applied to each of them. This sub-division is done also when the missing region is too large or the user wants to see more candidates to choose a better one. The multiple results from the sub-division are then ordered according to in-painting quality, which is measured based the edge map or discontinuity map along the boundary band. Our algorithm is demonstrated with various experiments using real images.

Keywords: image in-painting, band matching, seamless cloning, area sub-division.

1 Introduction

Digital image in-painting means a restoration or repairing of image areas which are missing or degraded accidentally or intentionally. This technique is also suitable for removing unwanted object regions or areas from movie frames as well as digital images; those areas are filled with similar textures or replaced by a new object digitally synthesized so as to, for example, ease the needs of re-shooting.

Image in-painting techniques can be categorized into two based on their fundamental approaches. The first category such as [1-3] adopts image intensity interpolation scheme based on PDE's (Partial Differential Equation), which are effective for filling-in small or narrow image regions because PDE-based interpolation provides a smooth continuation along the boundary very much naturally. This method is more appropriate for filling smoothly colored regions.

D. Mery and L. Rueda (Eds.): PSIVT 2007, LNCS 4872, pp. 180 – 190, 2007.

The second category [4,5,9,11,13,14,15,16] is about filling relatively larger regions using methods of texture synthesis. For example, the image region may be filled with a synthesized output texture image generated from a small input image using a technique of [6] or [10], trying to keep the continuity of boundary. This approach works well on regions with structural continuity. However, it is not effective on non-textured and smooth regions where structural continuity can be hardly defined. Among the work of the second category, this paper compares the algorithm and results with those of [4]. The seminal method of [4] fills the target region with many small patches one by one chosen on the ground of the priority and confidence computed based on image gradients or discontinuities. However, in order to attain a satisfactory result, the user needs to find a proper size of the small patch. Therefore, at least a few trial-and-decision loops are required for the user to reach at the final selection. The result of in-painting depends mainly on the size of the covering patch but the way of choosing the patch size is not discussed in [4]. Our study was inspired by this point. This paper on the contrary tries to fill a large missing region with only one large textured patch. That is, the proposed method tries to replace the whole target region with another whole image whose shape is the same as the target region. Some differences between [4] and ours are listed:

- In [4], the shape of image patch is rectangular and the image area for source-target matching is different from patch to patch. The patch size is determined by the user at the beginning of in-painting. We compare the colors of pixels in the boundary band and find the best matching according to the comparison. Only one band is considered at the beginning; the user need not choose the patch size. Furthermore, the computation speed becomes much faster in this case. We will present examples that show even this uncomplicated plain procedure works well.
- There is no process to guarantee the smoothness along the boundary in [4], which is not appropriate for in-painting when the target area is surrounded by smoothly graded colors. We overcome such cases by applying a seamless-cloning technique which is appropriate for stitching textured areas, too.
- When the user wants to see whether or not a better in-painting can be obtained, she/he has to increase or decrease the patch size and run the algorithm again for the case of [4]. Our method allows the user to choose the number of total patches to cover the in-painting area. For example, when it is two, the target is split vertically to form two patches and our band-based in-painting is performed; the same procedure is then applied to horizontally sub-divided patches; these result in two in-painted images in total. The user may choose one of them or increase the number to see more. Practically, as the number of sub-division increases, our method becomes similar to [4]. However, the basic philosophy of solving the in-painting problem is different as explained. Ours may be seen as a top-down approach in this sense whereas [4] and its followers can be taken as a bottom-up approach. The sub-division approach also provides a way of dealing with discontinuities inside the boundary band; priority map was developed in [4].

Section 2 explains our fundamental method: band-matching and seamless cloning. Experimental results of our method are also presented. They are fast in computation but show better results. Section 3 gives the detail of area sub-division method, which has two aims. The first is to provide practical usability; various in-painting results will be given to the users within fast computation time. The second is to guarantee the smoothness along the boundary band and hence reduce structural discontinuities along the boundary. Section 4 concludes this paper.

2 The Proposed In-Painting

Our image in-painting method consists of two basic components: band matching and seamless cloning. In band matching, defined is a band enclosing the boundary of a missing region. The band is compared to those from the other parts of the image. The inner image of the minimum difference band is then copied to the missing area. When the region is enclosed by textured surroundings, this procedure of band matching and copying the inside produces good in-painting result. The computation speed is very fast because band matching is the only necessary procedure. If the surroundings have smoothly colored parts, a noticeable non-smooth boundary (a seam) may happen. In this case, the seam between filled missing region and its neighborhood is removed by the procedure of seamless cloning. We found two seamless cloning algorithms applicable to our case in the literature [7,8,12] and we use the method of [7] due to its simplicity and effectiveness.

(a) (b) (c)

Fig. 1. (a) Input image (b) Enlarged image of input image: The white region is target region and the red contour is its boundary. (c) Marked target band: The blue region is target band.

2.1 Band Matching

As the initial step, the missing region (target region) is manually marked. For example, the white region in Figure 1 is the target region and the red contour is its boundary. The blue region around the target boundary contour is the band we are going to use for searching a source patch. That is, our idea is that a patch in the source image of a similar color or texture inside the boundary band will be a good patch for the area filling. The thickness of the band is set to five pixels for all the experiments in this paper. The target band is then compared to all the possible source bands

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

Fig. 2. An example of the proposed in-painting: (a) The target band (blue) is compared to the source ones (green). (b) The source band with minimum D_k (green) is found. (c) The target region is filled with the inner image of the optimal source band. (d) The result image.

throughout the whole image. The shape and thickness of a source band is the same as those of the target band. In Figure 2(a), green regions show some of the source bands.

Among the candidates of source bands, the optimal band is chosen as the one with minimum difference of color and gradient. Let k be the index to denote a source band and let C_k denote the difference of all the three color channels, G_k be the difference of gradients for the k-th source band, defined as following:

$$C_k = \sum_{i=1}^{N} \left|R_i^{S_k} - R_i^t\right| + \left|G_i^{S_k} - G_i^t\right| + \left|B_i^{S_k} - B_i^t\right| \tag{1}$$

$$G_k = \sqrt{\sum_c \left\|\nabla I_c\right\|}, \qquad c = \{R, G, B\} \tag{2}$$

where s and t stand for the source and target bands, respectively, N is the number of pixels belonging to the band, R, G and B mean the red, green, and blue color channels, respectively, and $\|\nabla I\| = \|(\nabla t_x - \nabla s_x,\ \nabla t_y - \nabla s_y)\|$; $\nabla t_x - \nabla s_x$ is the difference of horizontal gradients and $\nabla t_y - \nabla s_y$ is the difference of vertical gradients between target band and source band.

The similarity measure D_k between the target band and the k-th source band is given by a weighted sum of C_k and G_k as following:

$$D_k = \lambda_1 C_k + \lambda_2 G_k \tag{3}$$

where λ_1 and λ_2 are weight constants. If the difference of color is an important in the image, λ_1 will be larger than λ_2.

For every source patch, we choose the patch with minimum D_k. The selected source region is then copied the target region. In Figure 2(b), the green region is the source band with minimum D_k which is called the optimal source band. In Figure 2(c), the target region is filled with the inner image of the optimal source band, and Figure 2(d) is the final result. Figure 3(a) shows a magnified view of the in-painted area. Note that the in-painting was done by copying only without any boundary smoothing. In addition, our algorithm needs matching of those pixels inside the band over the source image only once, but such an image scanning is required for every patch in [4]. Accordingly, our algorithm results in a fast computation. For example, our method took 14 seconds for the computation with 812 pixels in the band area but our implementation of [4] took 4 minutes with the patch size 7x7 - 49 pixels.

Figure 4 shows more examples of our method. The band matching shows high performance on the images of repeated textures or similar colors. The middle example in Figure 4 tells that if all guitars are different, we selected a whole guitar instead of parts of guitar to an input image. The right-hand side example in Figure 4 also tells that if discontinuity appeared, we can solve it by target subdivision. Target subdivision will explain the section 3.

(a) (b)

Fig. 3. Comparison of the proposed method and that of [4]: (a) The result of the proposed (process time: about 14 sec.) (b) The result of [4] (process time: about 4 min.)

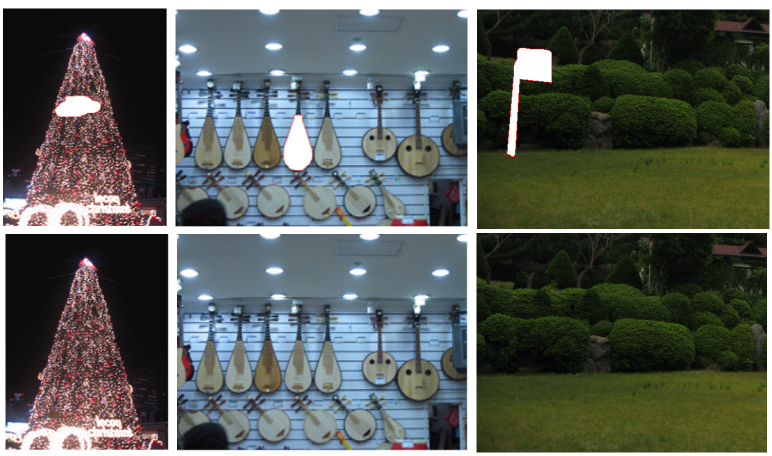


Fig. 4. The results of band matching: Upper line is input images and lower line is results of band matching. Computation time was 15, 26, 200 seconds, respectively. The number of band pixels is 1396, 1576, 2324 pixels, respectively. When [4] was applied, it took 420, 780, 1800 seconds.

2.2 Seamless Cloning

Seams along the stitching boundary are a great concern in developing an image in-painting algorithm. In particular, boundary seam occurs when the structure of the image is mainly composed of graded smooth colors. For example, direct stitching (copying) by band in-painting caused a visible seam in Figure 5. Main reason for this discontinuity is the difference of gradient as addressed in [7], [8] and [12]. In this paper, the discontinuity is made smooth by the seamless cloning algorithm proposed in [7]. We briefly introduce the method here.

Fig. 5. An example of discontinuous boundary: Left is the input, middle is the result of band-based in-painting, to which the seamless cloning is applied, and the right is the final result

For seamless cloning, we first compute $h(x,y)$, the ratio of pixel value of target band to the pixel value of the optimal source band along every boundary pixels *(x,y)*:

$$h(x, y) = \frac{f(x, y)}{g(x, y)} \tag{4}$$

where $f(x,y)$ and $g(x,y)$ are the pixel value of the target band and the optimal source band, respectively. Initial $h(x,y)$ inside the target region are set to 1. Then, the boundary values are propagated into the target area by repeatedly applying a Laplacian operator K:

$$h^n(x, y) = K \times h^{n-1}(x, y) \tag{5}$$

where n is the repetition index. Here we use K of size 3x3.

The final pixel value inside the target band is given by the product of updated $h(x,y)$ and the pixel value of the optimal source band.

$$\hat{f}(x, y) = h^n(x, y) g(x, y) \tag{6}$$

Figure 6 shows two more examples of band-based in-painting together with seamless cloning. Upper line shows results of in-painting by band matching, showing the seams on the boundary and lower line shows results of seamless cloning after band matching. It took 44 and 150 seconds, respectively. Note that this is still a very fast computation; when we applied the method of [4], it took 960 and 1260 seconds, respectively.

Fig. 6. The results of seamless cloning: Upper line is results of band matching and lower line is results of seamless cloning after band matching

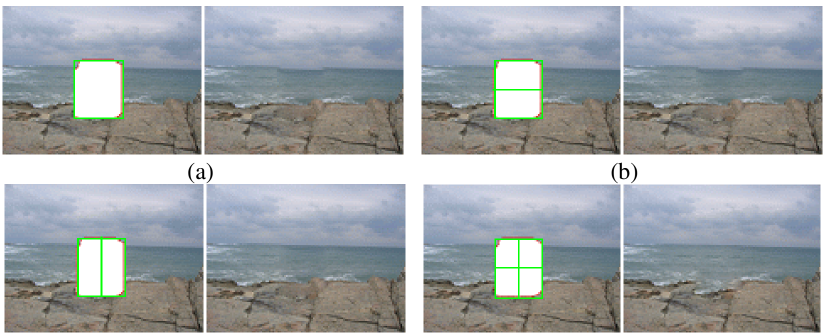
3 Target Sub-division and Quality Measure

There are some cases even the pair of band-based in-painting and seamless cloning may not resolve. If a line passes through the target region as shown in the left of Figure 7(a) for example, then there is a possibility where the line will appear to be discontinuous after in-painting as shown in the right of Figure 7(a). This is mainly due to the image structure and needs to be overcome for a realistic in-painting. On the other hand, in-painting is impossible when the target region is too large to perform our band matching because any of source bands cannot be found. For solving these problems we divide the target region into smaller ones as shown in Figure 7 and apply band matching and seamless cloning to each target subdivision region. This gives us a few various in-painting results according to the number of sub-divided target regions. For example, when the target is divided into two, we have two cases as shown in Figure 7(b)-(c). Therefore, we devise a method of measuring the quality of in-painting to decide the best of them or to list the results to help the user choose one among the results.

The number of subdivision is given by the number of horizontal cut and vertical cut, respectively. Figure 7 is an example; one horizontal cut resulting in two vertically divided pieces; one vertical cut, two horizontally divided. Therefore, in this case, we get four results; one without subdivision (Figure 7(a)), two with two subdivided targets (Figure 7(b)-(c)), and finally one with four sub-targets (Figure 7(d)). In Figure 7(a)-(d), each left image shows the way of target subdivision and each right image is the result of band in-painting. Notice that Figure 7(c) and Figure 7(d) look very much natural than the others because of the structural continuity provided by the subdivision band in-painting.

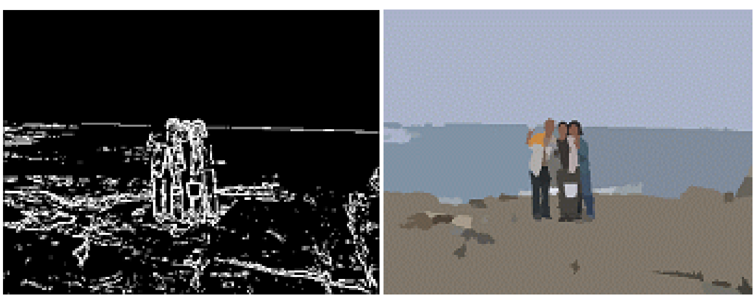
Actually, our advantage on the computational cost is partly due to the small number of pixels inside the band. If the degree of subdivision is high, our method will have many subdivided patches and the computational cost will become similar to that of [4]. However, at the user's viewpoint, there is a chance to have a good in-painting result when the degree is low with a short computation time. On the other hand, the total amount of computation until the degree becomes high is relatively low, which must be a very advantageous to practical users who have to execute an algorithm repeatedly to get a satisfactory result.

In order to measure the quality of each subdivision in-painting, for automatic selection on one hand and for user assistance on the other hand, this paper proposes two methods for computing the quality of results - the goodness of structural continuity. The first method uses edge maps of original image and the in-painted. The second uses segmentation instead of the edge map. In both of the methods, we check how the edges or the borders of different colors match along the in-painting boundary. This provides a measure for the structural continuity according to which we can sort out the multiple in-painting results.



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

Fig. 7. An example of target subdivision region into two for horizon and vertical respectively and its results: band matching using (a) one band, (b) and (c) two bands, (d) four bands



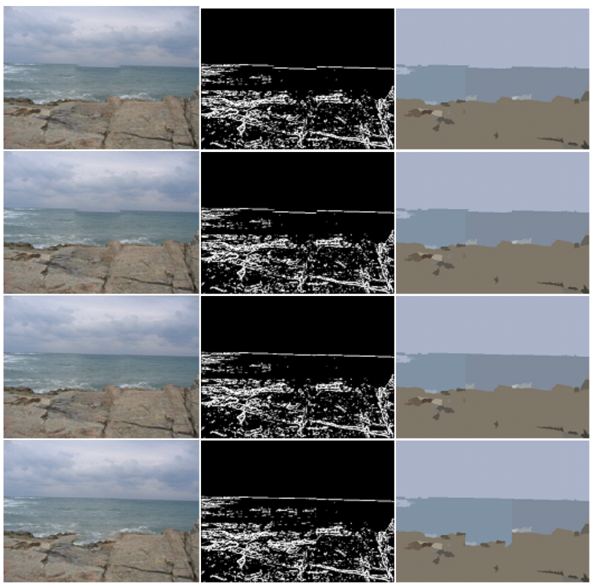
(a) (b)

Fig. 8. (a) Edge image (b) Segmentation image

The method using edge images is as following. First, we compute binary edge images by thresholding the magnitude of Sobel filtering; edges are marked white and the rest are marked black. Figure 8(b) is the edge image of the original image and

Figure 9(b) is of the in-painted images. Second, we define the comparison region to examine the edges of the original image and in-painting results. The comparison region is defined by target region's boundary and its front and rear pixels. Third, for each pixel in the comparison region, we compute $u(x,y)$, a sign for the structural difference; it is set to 1 if both of the edge maps have the same pixel values. Otherwise, it is set to 0. Finally, we sum up $u(x,y)$ to compute S_k, the measure of quality for the k-th in-painting result. The larger the value of S_k is, the better the in-painting result (or the better structural continuity) is.

Instead of the edge maps, we may use the results of color-based segmentation. Then, the borders of region segments play the same role as the binary edges. The remaining calculation process is identical. Figure 8(c) and 9(c) are segmentation images of the original image and in-painting results, respectively.



(a) (b) (c)

Fig. 9. (a) Original image (b) Edge image (c) Segmentation image

Fig. 10. Ordered results based on edge maps. Left was found to be the best.

Fig. 11. Ordered results based on color-based segmentation. Left was found to be the best.

Figure 10 and 11 shows the results of quality measure using edge maps and segmentation images, respectively. Left image had the highest score. For the examples in Figure 10 and 11, the two methods of quality measure provided the same computation. The right most in-painting result was from degree-four subdivision; the in-painted boundaries included highly textured area around the border of rocks and the sea, which made the quality low. However, the best quality by inspection was also chosen to be the best by our algorithm as shown in the figures.

4 Conclusion

We proposed an image in-painting algorithm using a kind of template matching between the target band and source bands. A band was a thick contour enclosing the region of the interest, and band matching itself found to be a very fast and useful in-painting algorithm. Seamless cloning was adopted to smooth the boundary. Our algorithm showed a fast and good performance compared to the previous method. Furthermore, we adopted the method of target subdivision in order to deal with the cases when target region was very large or the result of band-based in-painting was not good enough especially due to a structural continuity. We presented the performance of our algorithm with various experimental results.

Acknowledgments. This research is accomplished as the result of the research project for culture contents technology development supported by KOCCA and also supported by Seoul R&BD Program.

References

1. Bertalmio, M., Sapiro, G., Caselles, V., Ballester, C.: Image Inpainting. In: Proc. ACM SIGGRAPH, New Orleans, Louisiana, USA, pp. 417–424 (2000)
2. Bertalmío, M., Bertozzi, A., Sapiro, G.: Navier-Stokes, Fluid-Dynamics and Image and Video Inpainting. In: Proc. Conference on Computer Vision and Pattern Recognition, Hawaii, USA, pp. 355–362 (2001)
3. Chan, T., Shen, J.: Mathematical Models for Local Nontexture Inpaintings. SIAM Journal on Applied Mathematics, 1019–1043 (2002)

4. Criminisi, A., Perez, P., Toyama, K.: Object Removal By Exemplar-Based Inpainting. In: Proc. Conference on Computer Vision and Pattern Recognition, Wisconsin, USA, pp. 721–728 (2003)
5. Drori, I., Cohen-Or, D., Yeshurun, H.: Fragment-Based Image Completion. In: Proc. ACM Transactions on Graphics, SIGGRAPH, San Diego, California, USA, pp. 303–312 (2003)
6. Efros, A.A., Leung, T.K.: Texture Synthesis by Non-parametric Sampling. In: Proc. International Conference on Computer Vision, Kerkyra, Corfu, Greece, pp. 1033–1038 (1999)
7. Georgiev, T.: Covariant Derivatives and Vision. In: Proc. European Conference on Computer Vision, Graz, Austria, pp. 56–69 (2006)
8. Jia, J., Sun, J., Tang, C.K., Shum, H.Y.: Drag-and-Drop Pasting. In: Proc. ACM SIGGRAPH, Los Angeles, California, USA, pp. 631–637 (2005)
9. Komodakis, N., Tziritas, G.: Image Completion Using Global Optimization. In: Proc. Conference on Computer Vision and Pattern Recognition, New York, NY, USA, pp. 442–452 (2006)
10. Kwatra, V., Schodl, A., Essa, I., Turk, G., Bobick, A.: Graphcut Textures: Image and Video Synthesis Using Graph Cuts. In: Proc. ACM SIGGRAPH, San Diego, USA, pp. 277–286 (2003)
11. Perez, P., Gangnet, M., Blake, A.: PatchWorks: Example-Based Region Tiling for Image Editing, Technical Report MSR-TR-2004-04
12. Perez, P., Gangnet, M., Blake, A.: Poisson Image Editing. In: Proc. ACM SIGGRAPH, San Diego, California, USA, pp. 313–318 (2003)
13. Shen, J., Jin, X., Zhou, C., Wang, C.C.L.: Gradient Based Image Completion by Solving Poisson Equation. PCM, 257–268 (2005)
14. Sun, J., Yuan, L., Jia, J., Shum, H.Y.: Image Completion with Structure Propagation. In: Proc. ACM SIGGRAPH, Los Angeles, California, USA, pp. 861–868 (2005)
15. Wilczkowiak, M., Brostow, G.J., Tordoff, B., Cipolla, R.: Hole Filling Through Photomontage. In: British Machine Vision Conference, Oxford, UK, pp. 492–501 (2005)
16. Yamauchi, H., Harber, J., Seidel, H.P.: Image Restoration using Multiresolution Texture Synthesis and Image Inpainting. In: Proc. Computer Graphics International, Tokyo, Japan, pp. 120–125 (2003)