Image Inpainting Technique using Examplar-Based Blot Propagation

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Abstract- Image inpainting is the process of transfiguring an image in a form that is not catchable by a mediocre onlooker. There are many different processes to complete inpainting process. The most successful algorithms are geometric partial differential equations (PDEs), coherence among neighboring pixels, Transportation and Diffusion. Transportation is used to move pixels from outside to inside cracks. Diffusion propagates pixels from cracks borders like something hot (the image) moves into cold area (the cracked area). This paper presents a novel, highly adaptive and smooth algorithm to inpaint the defects such as spikes dirt and long vertical defect lines in the image. These defects may be produced in the image due to file development or improper maintenance of images. In this paper, examplar-based inpainting technique is used through blot propagation. This algorithm is using two steps to complete the inpainting process. These two steps are blot selection and blot inpainting.

Keywords- Image inpainting, Blot propagation, Blot selection, Blot tenuity, Blot priority, Tenuity representation

I. INTRODUCTION

The basic idea behind the inpainting process is to fill-in the gap of missing data in a form that it is not catchable by a mediocre observer. This process is called *inpainting.* Image inpainting has tremendous applications in digital effect (e.g., object removal), image restoration (e.g., scratch or text removal in photograph), image coding and transmission (e.g., recovery of the missing blocks), etc. In early days inpainting has been done by professional artists.

The most basic inpainting method is the diffusion based inpainting, in which the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. These algorithms are based on partial differential equation (PDE) and variation method. The diffusion-based inpainting algorithms have shown superb results to inpaint the non textured or relatively smaller missing region.

The second method is the examplar-based inpainting algorithm. This method propagates the image information from the known region into the missing region at the patch level. This idea is based on the texture synthesis technique. In this method, texture is synthesized by sampling the best match patch from the known region. However, natural images are the combination of structures and textures, in which the structures are having the primal sketches of an image (e.g., the edges, corners, etc.) and textures are having homogenous patterns including the flat patterns. Thus, the texture synthesis technique could not be able to inpaint the missing region which are combination of textures and structures.

Bertalmio *et al.* [1] proposed to divide the image into structure and texture layers and then inpaint the structure layer using diffusion-based method and texture layer using texture synthesis technique [2]. It overcomes the earlier problem of smooth effect of the diffusion-based inpainting method; however, it was still hard to inpaint larger missing structures. Criminisi *et al.* [3] proposed an examplar-based inpainting algorithm by propagating the known patches into the missing patches. Patch priority was defined to handle the missing region which was combination of textures and structures. Wu [4] proposed a cross-isophotes examplar-based inpainting algorithm, in which a cross isophotes patch priority term was designed which was based on the analysis of anisotropic diffusion. Wong [5] proposed a nonlocal means method for the examplar-based inpainting algorithm. The image patch was guessed by the nonlocal means of a set of candidate patches in the known region instead of a single best match patch. Other examplar-based inpainting algorithms [6]–[8] were also proposed for image inpainting. The examplar-based inpainting algorithms have given better results than the diffusion-based inpainting algorithm for the large missing region.

Recently, a new method, image sparse representation is also introduced [9]–[13]. The basic idea of this method is to represent image by sparse combination of an over complete set of transforms (e.g., wavelet, contourlet, DCT, etc.), then the missing pixels are guessed by adaptively updating this sparse representation. Guleryuz *et al.* [10]–[12]

proposed an image inpainting algorithm using adaptive sparse representation of image. However, similar to the diffusion based approach, it may fail to recover structure or introduce smooth effect when filling large missing region.

In this paper, examplar-based inpainting technique is used through blot propagation. This algorithm is using two steps to complete the inpainting process. These two steps are blot selection and blot inpainting. In the blot selection, a blot which is having the highest priority on the boundary (fill-front) of the missing region is selected for further inpainting. The priority is defined to encourage the filling-in of blot on structure such that the structures are more quickly filled than the textures. Then missing region which is combination of structures and textures can be inpainted properly [3], [14]. In the blot inpainting, the selected blot is inpainted by the candidate blot (i.e., examplars) in the known region.

II. PROPOSED ALGORITHM

Step 1: Take image I which is to be inpainted.
Step 2: Select the target region T.
Step 3: Compute the similarities for each pixel p of blot with its neighboring blots in the target region.
Step 4: Then compute the blot priority using structure tenuity.
Step 5: Now iterate the following steps until target region is inpainted-

- Choose the blot B which has highest blot priority.
- Now inpaint the chosen blot B using blot tenuity representation.
- Now update the target region T.
- For each pixel compute its blot similarities with the neighboring blots and its priority.

Step 5: The inpainted image will be obtained.

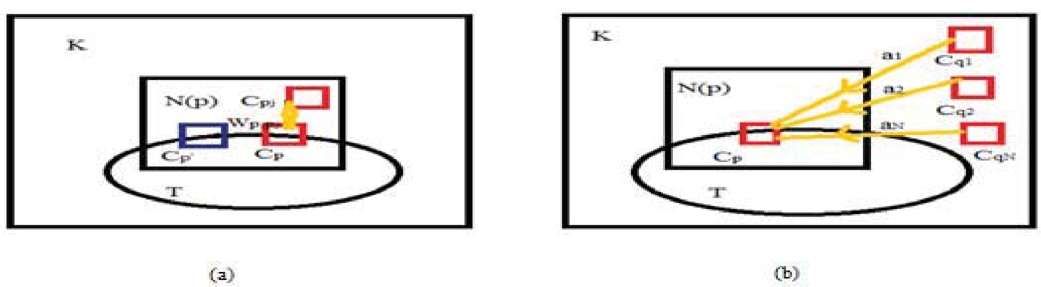


Figure 1. (a) Blot selection (b) Blot inpainting

here,
K: Known Region
T: Target Region
Cp: A blot centered at a pixel p
Cp’: A blot centered at a pixel p’
N(p): is a neighborhood window centered at p

III. INPAINTING BY EXAMPLAR-BASED BLOT PROPAGATION

3.1 *Blot Selection-*

For Blot Selection, blot priority should be defined and to define blot priority structure tenuity has been used here. The images are usually combination of structures and textures. A good definition of blot priority should be able to better distinguish the structures and textures, and also be durable to the orientation of the fill-front. We now define blot priority, i.e., structure tenuity.

3.1.1 Structure Tenuity: It is the measurement of rareness of the similarities of a blot with its neighboring blots. Structure tenuity is inspired by the following observations: structures are rarely distributed in the image domain, e.g., the edges and corners are distributed as 1-D curves or 0-D points in the 2-D image domain. Nevertheless, the textures are distributed in 2-D sub-regions of the image domain, which are frequently distributed. On the other hand, for a certain blot, its neighboring blots with larger similarities are also distributed in the same structure or texture as the blot of interest. Therefore, we can model the confidence of structure for a blot by measuring the rareness of its nonzero similarities to the neighboring blots. The blot with more rarely distributed nonzero similarities are prone to be located at structure due to the high rareness of structures.

3.1.2 Theorem: The structure tenuity for patch achieves the maximal value if a single nonzero similarity exists, and it achieves the minimal value if all the similarities are same. Firstly, to find the minimum value of W, we minimize W under the normalization constraint. It is easy to prove that W achieves minimal value when Wp,pj=1/|Ns(P)| for each pj. Then we maximize W. Due to the fact that 0<=Wp,pj<=1, so W<=1. The equality holds when only a single Wp,pj equals to 1, and all the other similarities equal to 0. So, W achieves its maximal value 1 when only a single similarity is nonzero and equals to 1. This theorem tells us that the structure tenuity achieves its maximum and minimum values when the blot similarities are distributed in the rarest and smoothest fashion respectively, and the structure tenuity increases with respect to the rareness of blot's nonzero similarities to its neighboring blots.

3.1.3 Structure Confidence: Structure confidence is used to show the reliability of color and intensity of blots. It is measured by structure tenuity. For the blot on the 0-D corners [e.g., Fig. 2(a)], it is saliently distributed within the local region; therefore, it has the highest structure trnuity. Due to the tenuity of image edges, the blot on 1-D edge [e.g., Fig. 2(b)] has similar blots rarely distributed along the same edge; therefore, they have higher structure tenuity. However, for the texture blots [e.g., Fig. 2(c) and (d)], they have similar blots in the 2-D local regions; therefore, they have smaller structure tenuity values. Under the guidance of structure tenuity, the blots located at structures (e.g., edges and corners) have higher priority for blot inpainting compared with the blots in texture regions.

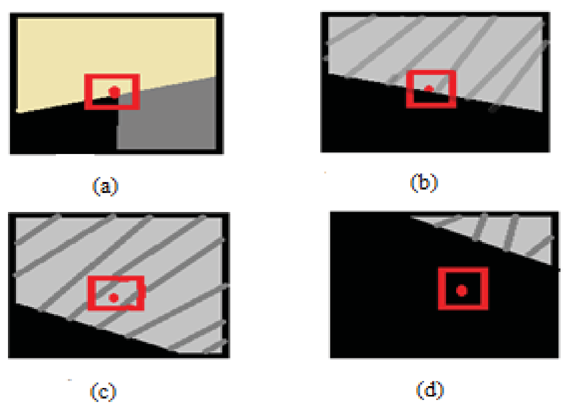


Figure 2. (a)Blot on corner (b) Blot on edge (c) Blot in texture (d) Blot in flat region

3.1.4 Blot Priority: The final blot priority is defined by multiplying the transformed structure tenuity term with blot confidence term. It is same defined as in [3] and [14]. It is initialized to 0 in the missing region or 1 in the known region. After each procedure of blot inpainting, the structure confidence of the newly filled pixels in the blots are updated by the confidence of the blot's central pixel. The inpainting algorithm is encouraged to firstly inpaint the blot located at image structures (i.e., edges or corners) and with larger confidence of its colors or intensities, then the target region with composite texture and structure can be more robustly inpainted.

3.2 Ishophote-based Priority -

Structure tenuity based priority is more reliable to identify the structure than the isophote-based priority [3], [14], which uses the inner product of isophote direction and the normal direction of the fill-front. Fig. 3 presents an example of inpainting for an image with composite textures and illusory edge. Fig. 3(a) shows the process of inpainting using isophote-based priority, and Fig. 3(b) shows the process of inpainting using structure tenuity based priority. The texture synthesis technique in [3] and [14] is incorporated for both cases. Using isophote-based priority, the blot at the top-right part of target region has the larger priority because the isophote direction is nearly same to the orthogonal direction of the fill-front at its central pixel. For example, the blot Ca in the texture region of the first image in Fig. 3(a) is with the highest priority, and the illusory edge is failed to be accurately recovered in the final result. However, structure tenuity based priority is able to robustly identify the structure regardless of the shape of fill-front. For example, the blot Cb in Fig. 3(b) along structure is with the highest priority using structure tenuity based priority, and the target region is inpainted perfectly in the final result.

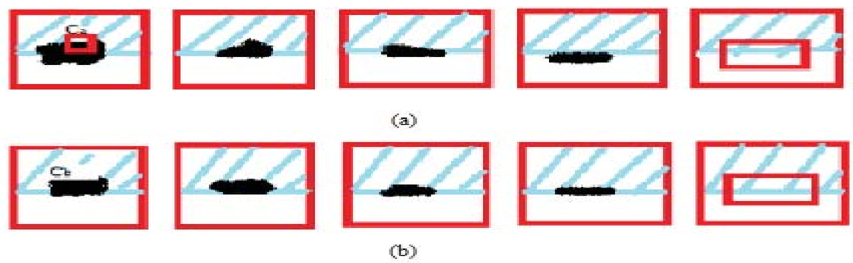


Figure 3. (a) Inpainting using isophote-based priority (b) Inpainting using structure tenuity-based priority

3.3 Blot Inpainting Using Blot Tenuity Representation –

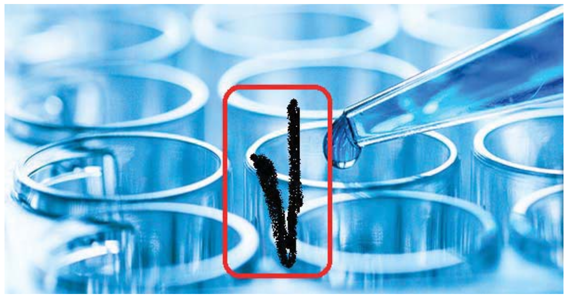
The blot, Cp on the fill-front with the highest blot priority is selected to be filled firstly. In the traditional examplar-based inpainting technique [3], [14], Cp is filled by sampling the best match blot from the known region. Recently, a nonlocal means approach [5] is proposed to fill in blot by the nonlocal means of several top similar blots instead of a single best match blot. Due to multiple samples are utilized, it is more reliable to estimate the missing information and produce better result. However, it tends to introduce smooth effect in the recovered image. In this work, we propose a novel model to inpaint blot by the rare combination of multiple examplars in the framework of rare representation. This method will achieve sharp inpainting result by rareness prior on the combination coefficients, and achieves consistent inpainting results with the surrounding textures by the constraints on the blot appearance in local neighborhood.

3.3.1 Blot Tenuity Representation: Given the blot Cp to be inpainted, a set of candidate patches [Cq]q=1to N, are sampled from the image source region, where N is the number of candidate blots for Cp. The candidate blots are selected as the top most similar blots.

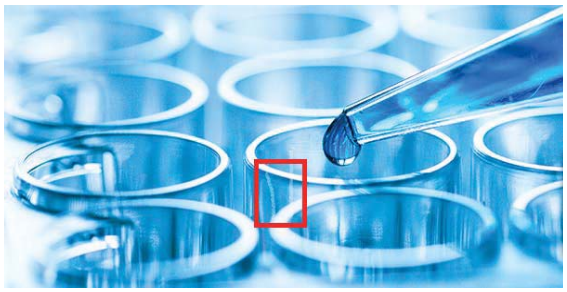
IV. EXPERIMENT AND COMPARISION

4.1 Experiment And Comparison For Scratch And Text Removal

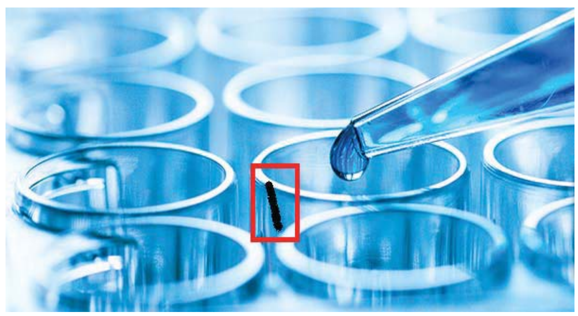
(a)



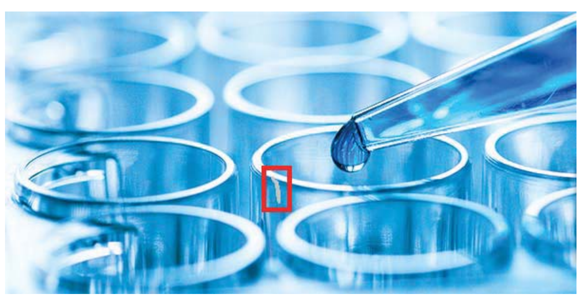
(b)



(c)



(d)



(e)

(f)

Figure 4. (a) Original image (b) Degraded image (c) Simultaneous texture and structure inpainting approach (PSNR=21.74) (d) Crimini's exampler-based approach (PSNR=16.47) (e) Wong's exampler-based approach (PSNR=20.87) (f) Proposed approach (PSNR=23.89)

Here, in Fig.4, the proposed inpainting algorithm is compared with the previous diffusion-based and examplar-based inpainting algorithms for scratch and text removal. It shows that the proposed method is showing better result than others.

4.2 Impact of Blot Tenuity on inpainting performance-

In this section, improvement in inpainting performance caused by structure tenuity and blot tenuity representation have been justified.

Table I Experiment Result

Examples	Wong[5]	Crimini[14]	Crim_spar[1]	Proposed algorithm
(a)	20.89	16.47	23.48	23.89
(b)	20.48	18.40	20.31	20.62
(c)	23.32	21.55	22.65	23.83
(d)	24.57	23.40	26.12	28.20
(e)	24.80	21.21	25.07	25.57
(f)	24.81	23.41	25.11	25.58
mean	22.81	20.26	23.53	24.42

V. CONCLUSION AND FUTURE WORK

This paper proposed a novel blot propagation based inpainting algorithm for scratch or text removal and missing block completion. This is inspired from the recent progress of the research in the fields of image sparse representation and natural image statistics. Structure tenuity was designed by measuring the rareness of the blot similarities in the local neighborhood. The blot with larger structure tenuity, which is generally located at the structure, tends to be selected for further inpainting with higher priority. On the other hand, the blot tenuity representation has been proposed to synthesize the selected blot by the rarest linear combination of candidate blots under the local consistency constraint. Comparisons showed that the proposed examplar-based blot propagation algorithm can better guess the structures and textures of the missing region, and produce sharp inpainting results consistent with the surrounding textures.

In the future, further investigation on the tenuity of natural images at multiple scales and orientations could be done and it could be applied on the image inpainting, super-resolution and texture synthesis. Incorporation of the human-labeled structures could also be done to recover the totally removed structures.

REFERENCES

[1] M. Bertalmio, L. Vese, G. Sapiro, and S. Osher, "Simultaneous structure and texture image inpainting," *IEEE Trans. Image Process.*, vol.12, pp. 882–889, 2003.
[2] A. Efros and T. Leung, "Texture synthesis by non-parametric sampling," in *Proc. Int. Conf. Comp. Vision*, 1999, pp. 1033–1038.
[3] A. Criminisi, P. Perez, and K. Toyama, "Object removal by examplarbased image inpainting," in *Proc. Int. Conf. Comp. Vision*, 2003, pp. 721–728.
[4] J.Wu and Q. Ruan, "Object removal by cross isophotes examplar-based image inpainting," in *Proc. Int. Conf. Pattern Recognition*, 2006, pp. 810–813.
[5] A. Wong and J. Orchard, "A nonlocal-means approach to examplar-based inpainting," presented at the IEEE Int. Conf. Image Processing, 2008.
[6] G. T. N. Komodakis, "Image completion using efficient belief propagation via priority scheduling and dynamic pruning," *IEEE Trans. Image Process.*, vol. 16, pp. 2649–2661, 2007.
[7] J. Jia and C. K. Tang, "Image repairing: Robust image synthesis by adaptive nd tensor voting," in *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recogition*, 2003, pp. 643–650.
[8] I. Drori, D. Cohen-Or, and H. Yeshurun, "Fragment-based image completion," *ACM Trans. Graph.*, vol. 22, no. 2003, pp. 303–312, 2005.
[9] M. Elad, J. L. Starck, P. Querre, and D. L. Donoho, "Simultaneous cartoon and texture image inpainting using morphological component analysis," *Appl. Comput. Harmon. Anal.*, vol. 19, pp. 340–358, 2005.
[10] O. G. Guleryuz, "Nonlinear approximation based image recovery using adaptive sparse reconstructions," presented at the IEEE Int. Conf. Image Processing, 2003.
[11] O. G. Guleryuz, "Nonlinear approximation based image recovery using adaptive sparse reconstructures and iterated denoising-part i: Theory," *IEEE Trans. Image Process.*, vol. 15, pp. 539–554, 2006.
[12] O. G. Guleryuz, "Nonlinear approximation based image recovery using adaptive sparse reconstructures and iterated denoising-part ii: Adaptive algorithms," *IEEE Trans. Image Process.*, vol. 15, pp. 555–571, 2006.
[13] M. J. Fadili, J. L. Starck, and F. Murtagh, "Inpainting and zooming using sparse representations," *The Comput. J.*, vol. 52, no. 1, pp. 64–79, 2009.
[14] A. Criminisi, P. Perez, and K. Toyama, "Region filling and object removal by examplar based image inpainting," *IEEE Trans. Image Process.*, vol. 13, pp. 1200–1212, 2004.