Volume 3, Issue 7, July 2013 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

The Examplar-Based Image Inpainting Algorithm through Patch Propagation

Pranali Dhabekar*
M.E. Student
E&TC Department& Pune University
Pune , India

Geeta Salunke , Meenu Gupta
Assistant Professor
E&TC Department& Pune University
Pune, India

Abstract— ***The filling-in of missing region in an image, which is Called image inpainting. Image inpainting is a technique for removing undesired objects in images and reconstructing the missing regions in a visually plausible way. Recently various approaches have been proposed a large variety of examplar based image inpainting algorithms to restore the structure and texture of damaged images. In this paper we introduce a novel and efficient exemplar based Image Inpainting Algorithm with investigating the sparsity of natural image patches. Two crucial steps of patch propagation are used in the examplar-based inpainting approach. First, to measure the confidence of a patch located at the image structure (e.g., the edge or corner) structure sparsity is designed at patch level. Second, it is assumed that the patch to be filled by the sparse linear combination of candidate patches under the local patch consistency of sparse representation. The patch with larger structure sparsity will be assigned higher priority for further inpainting. An improved priority term defines the filling order of patches in the image. In the proposed approach, Structure sparsity provides better discrimination of structure and texture, and the patch sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding textures.***

Keywords— ***Image inpainting, structure sparsity, sparse representation, confidence patch.***

I. Introduction

Natural images and photographs sometimes may contain stains or undesired objects covering significant portions of the images. Image inpainting is an iterative method for repairing damaged pictures or removing unnecessary elements from pictures. This activity consists of filling in the missing areas or modifying the damaged images in a non-detectable way by an observer not familiar with the original images. Region completion is a method to fill in such significant portions of an image by using the information from the remaining area of the image. Object removal from images is an image manipulation technique. The purpose of region completion varies from remove-undesired object to improve the quality of the image. The process of removing objects from images starts with mask out the undesired object, making the area where the object previously occupies a gap. Then the gap will be filled using graphical techniques. Among the graphical techniques that are used to fill the gap after object removal, two most commonly used are: image inpainting and texture synthesis.

The filling-in of missing information is very important in image processing, with applications including image coding and wireless image transmission (e.g.: recovering lost blocks) and image restoration (e.g.: scratch removal). It is an important image processing task in many real-life applications such as film restoration, text removal, scratch removal, and special effects in movies as well as image inpainting range from restoration of photographs, films and paintings, to removal of occlusions, such as large unwanted regions, superimposed text, subtitles, stamps and publicity, from images. In addition, it is of significant importance in restoration of precious work of arts, calligraphies, and paintings in the digital museum with image inpainting technique.

II. LITERATURE REVIEW

There have been many research works for the same and these works are classified into 2 major categories. One is non-exemplar based method and the other is examplar based method. The non-examplar based methods are based on pixel interpolation. Bertalmio first presented the notion of digital image inpainting and used third order Partial Differential Equations (PDE) to propagate the known image information into the missing regions along the direction of isophote (i.e., lines of equal gray values). The numbers of image inpainting techniques fill holes in images by propagating linear structures (called isophotes in the inpainting literature) into the target region via diffusion. They are inspired by the partial differential equations (PDE) of physical heat flow, and work convincingly as restoration algorithms. Chan and Shen considered the total variational (TV) inpainting model and curvature driven diffusion (CDD) model. The TV inpainting model stems from the well-known Rudin-Osher-Fatemi's image model and it fills in the missing regions such that the TV is minimized. Chan *et al*. introduced an inpainting technique using an Euler's elastica energy-based variational model. All these researches focused on inpainting in the pixel domain. Another category of approaches is the examplar based inpainting algorithm. This approach propagates the image information from the known region into the missing region at the patch level. Examplar-based methods, which have been successful in problems such as denoising and super resolution have also been found to give very good results for texture synthesis and inpainting. The usual approach to examplar based inpainting is to progressively fill in blocks on the boundary of the inpainting region using matching blocks in the known region of the same image.

Examplar based image inpainting algorithms are able to inpaint even for large regions and as well as natural scene images which have complex textures and structures. Therefore recently many examplar based inpainting methods have been developed. However, natural images are composed of structures and textures, in which the structures constitute the primal sketches of an image (e.g., the edges, corners, etc.) and the textures are image regions with homogenous patterns or feature statistics (including the flat patterns). Pure texture synthesis technique cannot handle the missing region with composite textures and structures. Bertalmio proposed to decompose the image into structure and texture layers, then inpaint the structure layer using diffusion-based method and texture layer using texture synthesis technique. It overcomes the smooth effect of the diffusion-based inpainting algorithm; however, it is still hard to recover larger missing structures.

Criminisi designed an examplar-based inpainting algorithm by propagating the known patches (i.e., examplars) into the missing patches gradually. To handle the missing region with composite textures and structures, patch priority is defined to encourage the filling-in of patches on the structure. Wu proposed a cross-isophotes examplar-based inpainting algorithm, in which a cross-isophotes patch priority term was designed based on the analysis of anisotropic diffusion. Wong proposed a nonlocal means approach for the examplar-based in this paper we have proposed an efficient examplar based image inpainting algorithm with an improved priority term that defines the filling order of patches in the image. The analysis of both theoretical and experimental results of examplar based algorithms provides a good framework. This idea stems from the texture synthesis technique proposed in which the texture is synthesized by sampling the best match patch from the known region. To improve the effect of results, Sun and Xu proposed a patch selection method by structure sparsity and a patch propagation method by sparse representation. Wohlberg proposed a competitive filling order estimating method by joint optimization of linear combinations of exemplars. The PDE-based algorithm does not perform well for texture dominated pictures. For such cases the examplar based algorithm is used instead. It gives us plausible results for inpainting the large missing regions.

III. DESIGN ARCHITECTURE

A. *System Design*

Software design is the process through which the requirements are translated into representation of software. Design is the technical kernel of the software engineering. During design, progressive refinements of data structure, program architecture, interfaces and procedural detail are developed, reviewed and documented. Design results in representations of software that can be assessed for quality.

B. *Architectural Design*

Architectural design involves identifying the software components, decoupling and decomposing then into processing modules and conceptual data structures and specifying the interconnections among the components.

Software architecture alludes to the overall structure of the software and the ways in which that structure provide conceptual integrity for a system. In its simplest form, architecture is the hierarchical structure of the program components (modules), the manner in which these components interact, and the structure of the data that are used by the components. The primary objective of architectural design is to develop a modular program structure and represent the control relationships between modules. In addition, architectural design melds program structure and data structure, defining interfaces that enable data to flow throughout the program.

The Architectural design of this work is presented in the following specification.

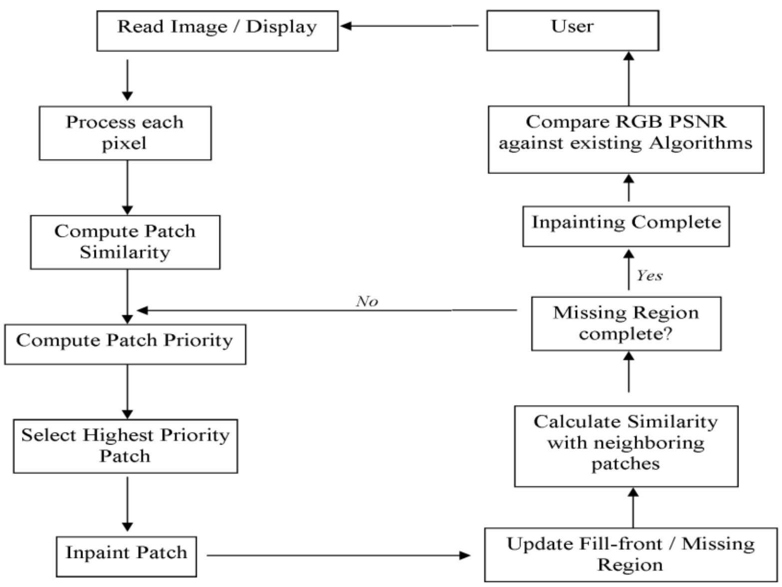


Fig. 1 Architecture Design

IV. PROPOSED WORK

A. *Novel Examplar Based Image Inpainting*

This paper we introduce a novel examplar based Image Inpainting Algorithm with an improved priority term which defines the filling order of patches in the image. This algorithm is based on patch propagation by propagating the image patches from the source region into the interior of the target region patch by patch.

The novel examplar-based model is proposed because it uses a cross-isophote diffused PDE to constrain the processing order; therefore, it has a good linear structure preserving property. The size of exemplar is dynamically determined by the local textured information; the seams and block effects are removed by the PDE. Because the examplar-based model could not be used for complex geometric structures completion, the novel model adopts a bi-directional diffused PDE to assist the completion procedure. Then the novel model could be used to restore the natural image with both large target regions and complex geometric structures.

B. *Patch Propagation*

In our proposed algorithm, the examplar-based inpainting algorithm through patch propagation. The two basic procedures of patch propagation are:

- Patch selection
- Patch inpainting.

In the patch selection, a patch on the missing region boundary with the highest priority is selected for further inpainting. The priority is defined to encourage the filling-in of patches on structure such that the structures are more quickly filled than the textures, then missing region with composite structures and textures can be better inpainted. Traditionally, the patch priority is defined based on the inner product between isophote direction and the normal direction of the missing region boundary.

In the patch inpainting, the selected patch is inpainted by the candidate patches (i.e., examplars) in the known region. The approach in Criminisi's examplar-based algorithm, P. Perez, and K. Toyama utilizes the best match candidate patch to inpaint the selected patch. The approach Wong's examplar-based algorithm uses a nonlocal means of the candidate patches for robust patch inpainting. To better address the problems of patch selection and patch inpainting, two novel concepts of patch sparsity of natural image, are proposed and applied to the examplar-based inpainting algorithm.

- Patch Structure Sparsity
- Patch Sparse Representation

First, we define a novel patch priority which is based on the sparseness of the patch's nonzero similarities to its neighboring patches. This sparseness is called **structure sparsity of patch**. Compared with the priority defined on isophote, this definition can better distinguish the texture and structure, and be more robust to the orientation of the boundary of missing region.

Second, to inpaint a selected patch on the boundary of missing region, we use a sparse linear combination of examplars to fill the patch. That means only very few examplars contribute to the linear combination of patches with nonzero coefficients. This representation is called **patch sparse representation**. The patch sparse representation is also constrained by the local patch consistency constraint. Such type of sparseness prior has been successfully applied to the image denoising, super-resolution, inpainting, deblurring and so on. The structure sparsity also models the sparsity of natural image. However, it models the sparseness of nonzero similarities of a patch with its neighboring patches instead of high-frequency features.

Our proposed method includes the following steps

1. Initialization of Target region
   This is done by marking the target region by some special colour without any loss of generality.
2. Edge Detection of target region.
3. Patch selection from the target region for inpainting.
4. Best matched patch selection from the source region.
   A suitable error metric called Mean Square Error is used to find the best matching patch.
5. Updating the image information according to step.

V. INPAINTING ALGORITHMS

A. *Patch selection*

In this section, we will describe and define the priority term for patch selection in detail. Given an image I with the missing region Ω and the known region $\overline{\Omega}$, the task of image inpainting is to fill in the target region (i.e., the missing region Ω) using the image information in the source region (i.e., the known region $\overline{\Omega}$). The boundary of the target region is denoted by $\partial\Omega$, which is called the fill-front in the examplar-based inpainting algorithm. We further denote as Ψ_p a patch centered at a pixel p.

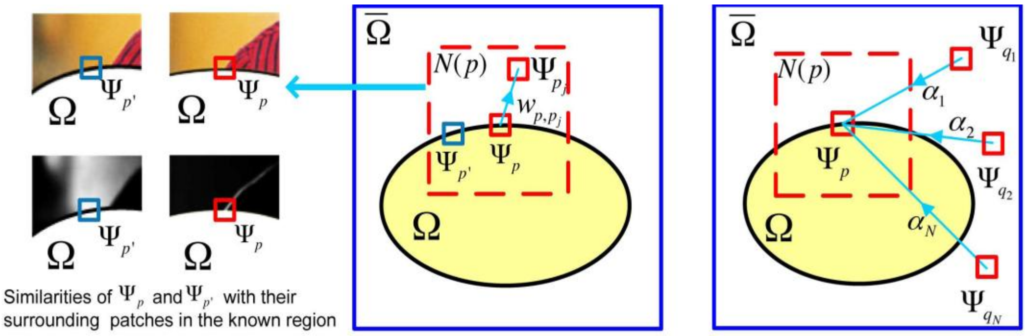


Fig.2. (a) Patch Selection (b) Patch Inpainting

The centre point p of this patch is located at the boundary of target region. This is called a target patch. Some areas of this target patch are known regions where as others need to be repaired. The priority of the target patch will decide the order of repair region. The target patch which has the highest priority should be repaired first. So, we should compute the priority of target patch. When all priorities of the target patch have been computed, we find the patch Ψ_p with highest priority.

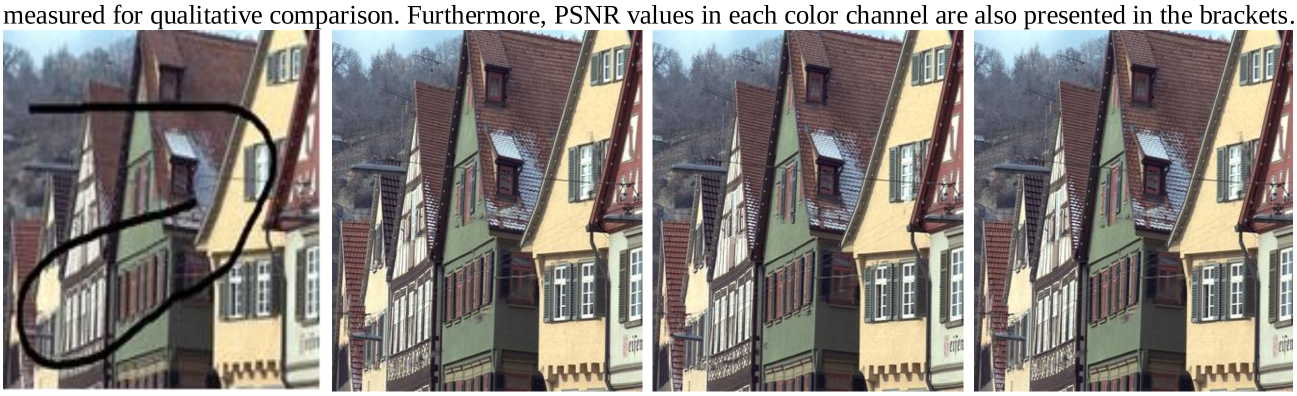
In the patch inpainting, the selected patch is inpainted by the candidate patches (i.e., examplars) in the known region. In this section, we will describe and define the Propagation of Exemplars. When all priorities of the target region have been computed, we find the patch Ψ_p with highest priority. Then, we fill it with the source region φ which is the most similar to Ψ_p. The exemplar based propagation is conducted to recover the missing pixels in the selected patch Ψ_p several exemplar patches Ψ_{qi} are selected and missing pixels in Ψ_p are propagated by synthesizing corresponding pixels in Ψ_{qi}

VI. PERFORMANCE EVALUATION

In this section, we test the proposed examplar-based patch propagation algorithm on a variety of natural images. We apply our algorithm to the applications of scratch/text removal, object removal and block completion. In these examples, we compare our algorithm with the Criminisi's examplar-based approach, Wong's examplar-based approach, and our proposed approach. PSNR values of the inpainted image and its each colour channel (shown in bracket for (R, G, B channels) are presented for each result.

A. *Experiments and Comparisons for Scratch Removal*

Fig3. House Image, Fig.4. Leena Image & Fig.5 Bungee Image presents examples for scratch removal, Block Completion & Object removal. In this fig,(a) shows the degraded image, and remaining fig.[(b),(c),(d)] Shows the result of Criminisi's examplar-based inpainting algorithm , Wong's examplar-based inpainting algorithm, and proposed algorithm respectively. Peak signal-to-noise ratio (PSNR) between the inpainted images and the original images are measured for qualitative comparison. Furthermore, PSNR values in each color channel are also presented in the brackets.



(a) Degraded image PSNR=15.81 (15.92, 15.45, 16.08) PSNR=16.15 (16.22, 15.87, 16.37) PSNR=17.21 (17.39, 16.90, 17.36)
(b) Criminisi's ex. approach (c) Wong's ex. approach (d) Proposed method

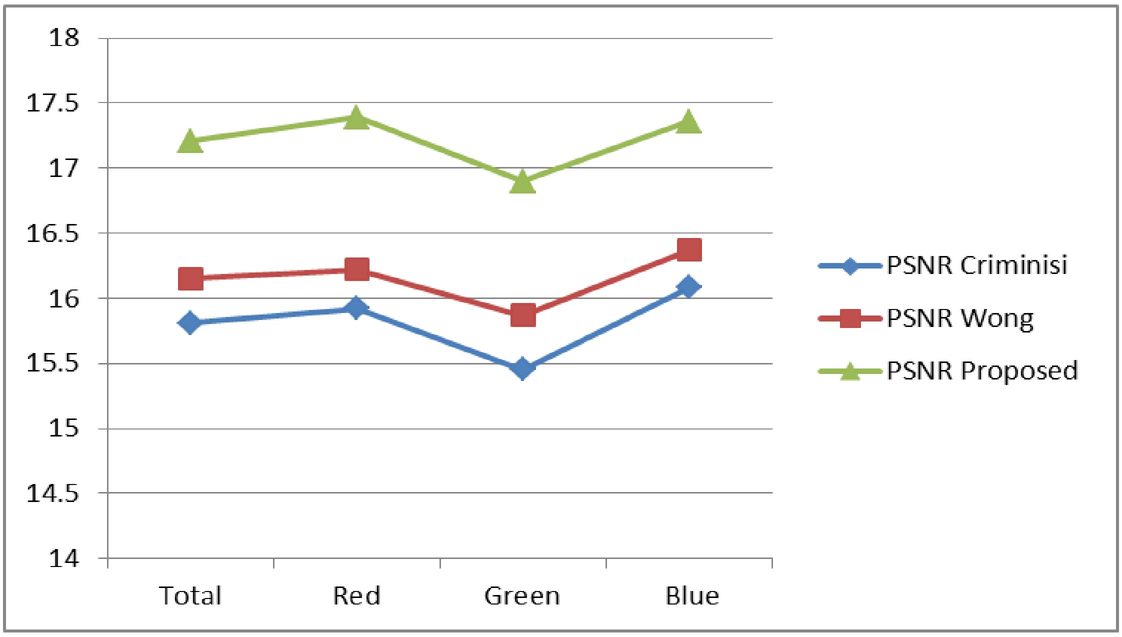
Fig3 House Image

As shown in Fig.3 Used to Present Example of scratch removal. The Criminisi's examplar-based inpainting algorithm produces sharp inpainting results shown in fig. (b). However, due to the fact that only a single best match patch is used, some unpleasant artifacts are introduced in the results. For example, the unwanted structure appears within the image of Criminisi's result in the fig. (b) Of Fig.3.

The Wong's algorithm produces more pleasant results because more candidate patches are combined. For example, the unwanted structure shown in the fig (b) Of Fig.3 is alleviated in the result of Wong's algorithm.

Table No.1 Experimental result of PSNR values for House Image

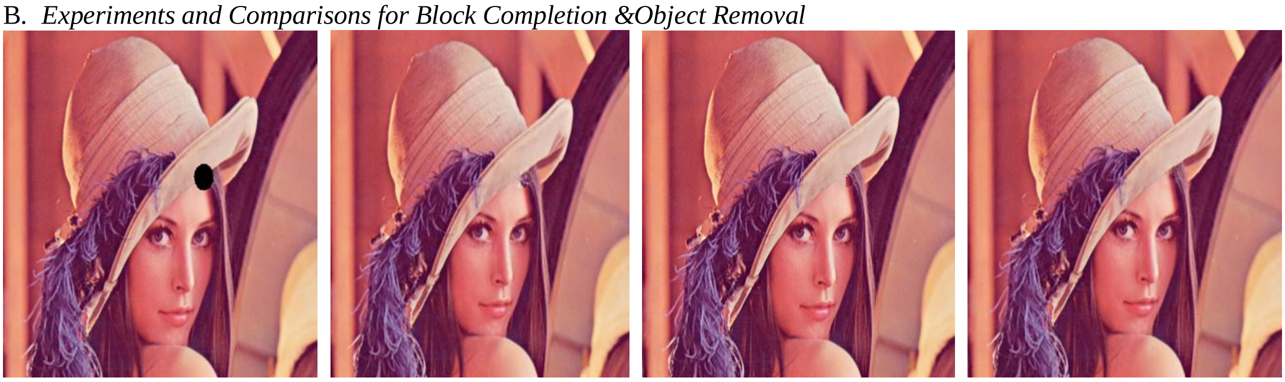
Channel	PSNR Criminisi	PSNR Wong	PSNR Proposed
Total	15.81	16.15	17.21
Red	15.92	16.22	17.39
Green	15.45	15.87	16.90
Blue	16.08	16.37	17.36



Graph of fig.3. Effect of PSNR for Picture of House image

In Fig.3 Our proposed algorithm in fig.(d), the patch priority is defined more robustly, and the candidate patches are adaptively combined in the framework of sparse representation, it achieves sharp and consistently better inpainting results with the best PSNR values. PSNR values of the inpainted image and its each color channel (shown in bracket for (R, G, B channels) are presented for each result. It shows the result R, G, B Channel values of Criminisi's examplar-based inpainting algorithm, Wong's examplar-based inpainting algorithm, and proposed algorithm.

B. *Experiments and Comparisons for Block Completion &Object Removal*



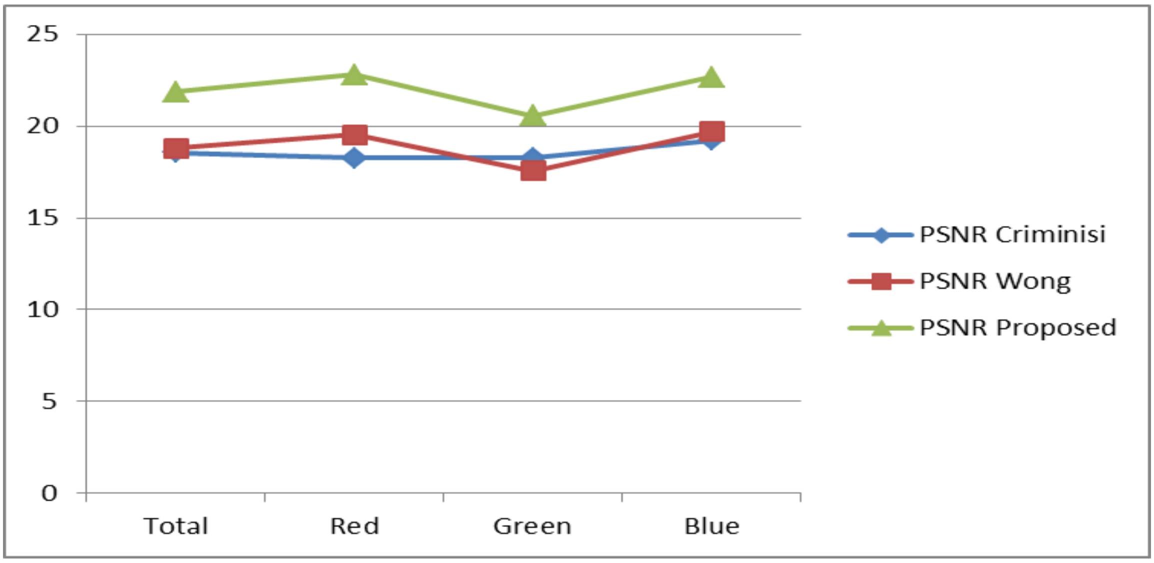
Degraded Image PSNR=18.55 (18.24, 18.25, 19.22) PSNR=18.80 (19.51, 17.55, 19.69) PSNR=21.87 (22.78, 20.56, 22.66)

Criminisi's ex. approach Wong's ex. approach Proposed method

Fig 4. Leena Image

Table No.2 Experimental result of PSNR values for Leena Image

Channel	PSNR Criminisi	PSNR Wong	PSNR Proposed
Total	18.55	18.80	21.87
Red	18.24	19.51	22.78
Green	18.25	17.55	20.56
Blue	19.22	19.69	22.66



Graph of fig.4. Effect of PSNR for Picture of Leena image

C. *Example of Object Removal*

Degraded Image PSNR=18.78 (18.25, 18.60, 19.50) PSNR=18.92 (19.40, 17.60, 19.78)
PSNR=21.83 (23.37, 19.89, 22.24)

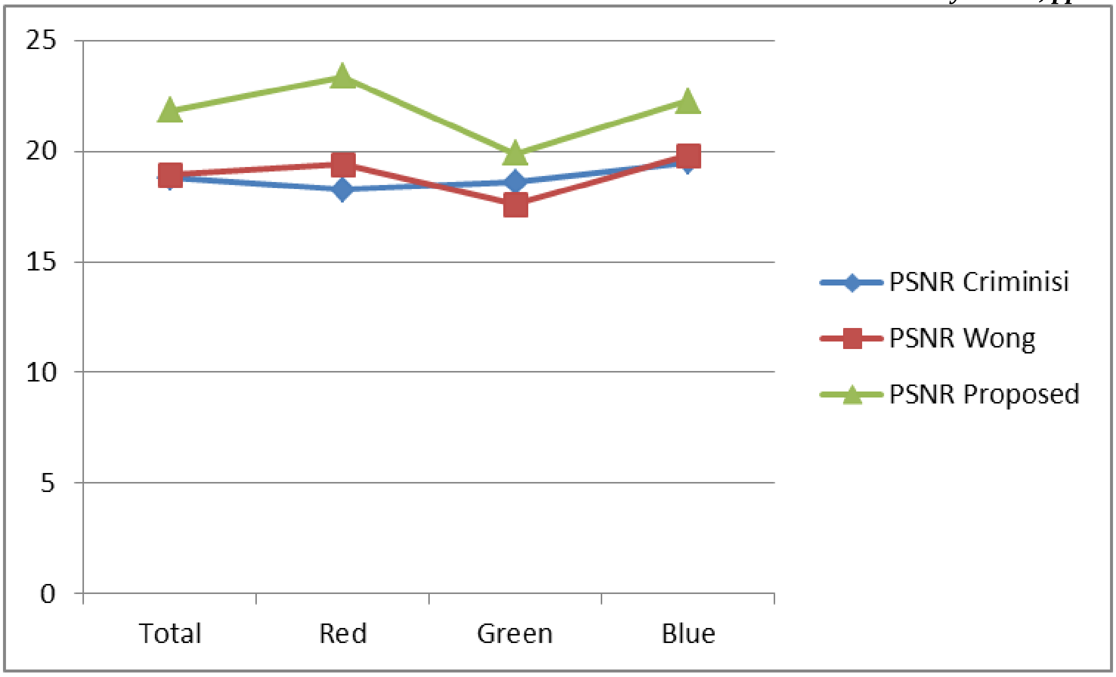
Criminisi's ex. Approach Wong's ex. approach

Proposed method

Fig 5. Bungee Image

Table No.3 Experimental result of PSNR values for Bungee Image

Channel	PSNR Criminisi	PSNR Wong	PSNR Proposed
Total	18.78	18.92	21.83
Red	18.25	19.40	23.37
Green	18.60	17.60	19.89
Blue	19.50	19.78	22.24



Graph of fig.5. Effect of PSNR for Picture of Bungee image

In Fig.4 & Fig.5 presents two examples of block completion & Object removal respectively. We now apply the proposed algorithm to inpaint the missing region after object removal. We also compare the proposed algorithm with the related examplar-based inpainting algorithms. In the results of Criminisi's algorithm, the inpainted patches are not always consistent with the surrounding textures, The Wong's algorithm uses several top best examplars to infer the unknown patch, so the results have less effect of patch inconsistency. However, it introduces smooth effect as shown in the results. As for the proposed algorithm, local patch consistency is constrained, so the inpainted patches are more consistent with the surrounding textures. In addition, the patch is inferred by the sparse combination of candidate patches, so the results have rare smooth effect in appearance.

VII. Conclusions

This paper proposed novel patch propagation based inpainting algorithm for scratch removal, object removal and missing block completion. The major novelty of this work is that two types of patch sparsity were proposed and introduced into the examplar-based inpainting algorithm Structure sparsity was designed by measuring the sparseness of the patch similarities in the local neighborhood. The patch larger structure sparsity, which is generally located at the structure, tends to be selected for further inpainting with higher priority. Experiments and comparisons showed that the proposed examplar-based patch propagation algorithm can better infer the structures and textures of the missing region, and produce sharp inpainting results consistent with the surrounding textures

References

[1] M. Bertalmio, G. Sapiro, V. Caselles, and C. Ballester, "Image inpainting," in *Proc. SIGGRAPH*, 2000, pp. 417–424.

[2] M. Bertalmio, A. L. Bertozzi, and G. Sapiro, "Navier–Strokes, fluid dynamics, and image and video inpainting," in *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2001, pp. 417–424.

[3] T. Chan and J. Shen, "Local inpainting models and tv inpainting," *SIAM J. Appl. Math.*, vol. 62, no. 3, pp. 1019–1043, 2001.

[4] T. Chan and J. Shen, "Non-texture inpainting by curvature-driven diffusions,"*J. Vis. Commun. Image Represent.*, vol. 4, no. 12, pp. 436–449, 2001.

[5] C. Bertalmio, M. Bertalmio, V. Caselles, G. Sapiro, and J. Verdera, "Filling-in by joint interpolation of vector fields and gray levels," *IEEE Trans. Image Process*, vol. 10, pp. 1200–1211, 2001.

[6] A. Levin, A. Zomet, and Y. Weiss, "Learning how to inpaint from global image statistics," in *Proc. Int. Conf. Comp. Vision*, pp. 305–313.

[7] S. Roth and M. J. Black, "Fields of experts: A framework for learning image priors," in *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2005, pp. 860–867.

[8] S. Roth and M. J. Black, "Steerable random fields," in *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2007, pp.18.

[9] A. Efros and T. Leung, "Texture synthesis by non-parametric sampling," in *Proc. Int. Conf. Comp. Vision*, 1999, pp. 1033–1038.

[10] 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.

[11] A. Criminisi, P. Perez, and K. Toyama, "Object removal by examplarbased image inpainting," in *Proc. Int. Conf. Comp. Vision*, 2003, pp. 721728.

[12] J.Wu and Q. Ruan, "Object removal by cross isophotes examplar-based image inpainting," in *Proc. Int. Conf. Pattern Recognition*, 2006, pp. 810– 813.

[13] A. Wong and J. Orchard, "A nonlocal-means approach to examplar based inpainting," presented at the IEEE Int. Conf. Image Processing, 2008.

[14] 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.

[15] 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 Recognition*, 2003, pp. 643–650.

[16] I. Drori, D. Cohen-Or, and H. Yeshurun, "Fragment-based image completion," [17] 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.

[18] O. G. Guleryuz, "Nonlinear approximation based image recovery using adaptive sparse reconstructions," presented at the IEEE Int. Conf. Image Processing, 2003.

[19] 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.

[20] 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.

[21] 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.

[22] 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.

[23] Y. P. Li and D. Huttenlocher, "Sparse long-range random field and its application to image denoising," presented at the European Conf. Computer Vision, 2008.

[24] M. F. Tappen, B. C. Russell, and W. T. Freeman, "Exploiting the sparse derivative prior for super-resolution and image demosaicing," presented at the IEEE Workshop on Statistical and Computational Theories of Vision, 2003.

[25] J. Sun, J. Sun, Z. B. Xu, and H.-Y. Shum, "Image super-resolution using gradient profile prior," presented at the IEEE Computer Society Conf. Computer Vision and Pattern Recogition, 2008.

[26] Z. Xu and J. Sun, "Image inpainting by patch propagation using patch sparsity," IEEE Transactions on Image Processing, vol. 19 no.5, pp. 1153- 1165, May 2010.