A Novel Exemplar based Image Inpainting Algorithm for Natural Scene Image Completion with Improved Patch Prioritizing

K. Sangeetha Assistant Professor Department of CA, BIT, Sathy - 638 401, Tamilnadu, India Dr. P. Sengottuvelan Associate Professor Department of IT, BIT, Sathy - 638 401, Tamilnadu, India E. Balamurugan Assistant Professor Department of CA, BIT, Sathy - 638 401, Tamilnadu, India

ABSTRACT

Image Inpainting is the process of filling in missing regions in an image. The objective of inpainting is to reconstruct the missing regions in a visually plausible way. Several algorithms are available in the literature for the same. Many researchers have proposed a large variety of exemplar based image inpainting algorithms to restore the structure and texture of damaged images. In this paper we introduce a novel exemplar based Image Inpainting Algorithm with an improved priority term that defines the filling order of patches in the image. This algorithm is based on patch propagation by inwardly propagating the image patches from the source region into the interior of the target region patch by patch. Experiment results show that our proposed exemplar based image inpainting algorithm performs well compared with other existing algorithms on the basis of Peak Signal to Noise Ratio (PSNR). The results are found to be highly competitive with other recent inpainting methods.

Keywords: Image inpainting, Exemplar based, Patch Propagation, PSNR.

1.INTRODUCTION

Removing objects and repairing damaged regions are very interesting and tedious task. Image inpainting is a technique for removing undesired objects in images and reconstructing the missing regions in a visually plausible way. 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 exemplar based method. An overview of these methods is found in [6-8].

The non exemplar based methods are based on pixel interpolation [1-5]. Bertalmio et al [1] 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. Later [1], this inpainting approach was modified to take into account the Navier-Stokes flow [2]. Some other algorithms of this category are presented in [3-7].

These are effective for small missing regions like small scratches in a photograph and not suitable for large missing regions.

The second category of approaches is the exemplar based inpainting algorithm. This approach propagates the image information from the known region into the missing region at the patch level. Exemplar-based methods, which have been successful in problems such as denoising [10], [11] and super resolution [12], [13] have also been found to give very good results for texture synthesis and inpainting [8-9], [14]. The usual approach to exemplar 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 [9], [14-16].

Exemplar 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 exemplar based inpainting methods have been developed. In this paper we have proposed an efficient exemplar 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 exemplar based algorithms [23] provides a good framework for us to extend our contribution to this category. This idea stems from the texture synthesis technique proposed in [9] in which the texture is synthesized by sampling the best match patch from the known region.

The rest of the paper is organized as follows: Section 2 presents the process of general exemplar based algorithm used in the literature and section 3 includes a description of our proposed method. The experiment results are shown in section 4 and finally the conclusion is presented in section 5.

2.BACKGROUND AND REVIEW OF EXEMPLAR BASED INPAINTING

In this section we briefly review the exemplar based image inpainting algorithms. In the past decade there has been considerable work concerned with image inpainting. The fill order is chosen to minimize artifacts by giving priority to patches containing significant edges leading into the inpainting region.

Criminisi et al [9] designed an exemplar based inpainting algorithm by propagating the known image patches (i.e., exemplars) into the missing patches gradually. The method of Wexler et al [17] may also be considered as a global optimization, it is defined and computed in an entirely different way, and it gives significant different behavior in difficult in-painting examples.

To improve the effect of results, Sun and Xu [14] proposed a patch selection method by structure sparsity and a patch propagation method by sparse representation. Wohlberg [21] proposed a competitive filling order estimating method by joint optimization of linear combinations of exemplars.

Zhaolin Lu [18] proposed a PDE-based image completion algorithm in which the geometrical property of an image structure is preserved. More examplar-based inpainting algorithms [19-22] were also proposed for image completion.

Figure1 shows the notation used by Criminisi. The original image I has M*N pixels. The target region to be inpainted is denoted by Ω . The source region is represented by Φ where $\Phi = I-\Omega$. The boundary in the target region is denoted by $\delta\Omega$.

In general an exemplar based image inpainting algorithm has the following steps.

1) For each point p in the boundary $\partial \Omega$, find the following

(a) Data term D (p) =
$$\left| \nabla_{\mathbf{I}} \frac{\mathbf{I}}{\mathbf{P}} \cdot n_{p} \right|$$

where $\nabla I \stackrel{\perp}{p}$ is the isophote of intensity at p and n_p is the unit vector orthogonal to boundary $\partial \Omega$ at p.

- (b) Confidence term C (p) = $\sum q \varepsilon \psi$ (p).C (q) for the patch ψ_p centered at the pixel p.
- (c) The inpainting priority of p is denoted as $P(p) = C(p) \cdot D(p)$. where C (p) is set to C (p) =0, $\forall p \in \Omega$

and C(p)=1, $\forall p \in I-\Omega$ as in fig 2.

- 2) Select the highest priority point p in $\partial\Omega$ and then search to find a patch ψ_q which is most similar to ψ_p and copy the patch to the target area.
- 3) Continue the above steps till all points in the inpainting domain are completed.





3. THE PROPOSED METHOD

The result of any exemplar based inpainting algorithm highly depends on the patch selection which is to be inpainted and for this selection order of patches must be defined. To improve the results we have provided an approach that defines an efficient priority term for patch prioritizing. The proposed algorithm is based on patch propagation by inwardly propagating the image patches from the source region into the interior of the target region patch by patch. For each iteration, the algorithm is decomposed into two procedures as 1) patch selection and 2) patch inpainting.

In this section, we will describe and define the priority term for patch selection in detail. We assume I be the original image which includes a target region Ω which is to be inpainted and a source region Φ (Φ =I- Ω) where patches are searched and used. Hence I= $\Phi \cup \Omega$, a contour of the target region is denoted by $\delta\Omega$. The patch ψ_p centered on the point p:

We use a 9*9 patch, the centre point p of this patch are located at the boundary of target region. This is 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. The target patch which has the highest priority should be first repaired. 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.

Our proposed method includes the following steps

- 1. Target region initialization
 - This is done by marking the target region in some special colour without any loss of generality.
- 2. Detection of target region boundary.
- 3. Patch selection from the target region for inpainting.

Here we have taken a default patch size as 9*9and the selected patch is denoted as ψ_{p} .

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 4.

The proposed method is described in detail as follows:

3.1 Computing Patch Priorities and Patch Selection

3.1.1 Patch Prioritizing

In the procedure of patch selection, patch priority should be defined to encourage the filling-in of patches on the structure with highest priority. Confidence term can serve as a measure of the amount of reliable information surrounding the pixel point p in an image. When this point is surrounded by many pixels from the original image, the more reliable information from the source region is contained within the patch that is matched.

In Criminisi et al's algorithm, the best patch can be selected by using the priority function P(p) which is defined as the sum of two factors. P(p)=C(p)*D(p).

Instead of using this multiplicative definition, we have proposed the addition of weights to the priority term as P(p)=a*RC(p)+b*D(p) for $0\le a, b\le 1$ and a+b=1

where a is the component weight for C(p) and b is the component weight for D(p). The regularized confidence term RC(p) is denoted as $RC(p)=(1-\omega)*C(p)+\omega$ for $0\le \omega\le 1$

where ω is the regularizing factor for controlling the curve smoothness. By changing the priority for the patches on the $\delta\Omega$ now we are able to find a patch ψ_p with the highest priority.

Here, we use a default mask size of 9×9 pixel as an exemplar region. We will compute the priority of each pixel on the boundary from the target region, and then according to the level of the priority order to sequentially fill in the patch information. Finally, the priority of the boundary in the target region will be updated.

Fig 2. Boundary confidence value set.



3.1.2 Search for the best matched patch

Most often, the patch that most resembles the selected patch lies very close to the patch selected to be inpainted. Based on this assumption, we provide an approach on how to reduce the computational complexity of the algorithm.

For the patch ψ_p with highest priority, we would find the best matched patch of it in Φ . To increase the robustness of the similarity between exemplar patch and matching patch based on the square of Euclidean distance we design a new similarity matching function. The diameter of the surrounding region to search is calculated at run time by taking into account the region to be inpainted.

We search for the best exemplar from a rectangle defined by (P1, P2) and (Q1, Q2). These coordinates can be found as follows:

> P1=max (0, p-pc/2-cpr-MDx/2) P2= max (0, p- pr/2-cpc-MDy/2) Q1=min (width, p+cpr/2+cpr+MDx/2) Q2=min (height, p+ cpc/2+cpc+MDy/2)

The diameter of the search region is calculated at run time.pr and pc are the number of rows and columns in the patch. MDx and MDy are constants that represents minimum diameter for the X and Y directions respectively.cpr and cpc are the number of continuous green (which has been used as target mask) pixels.

In the process of searching for the best matching patch, we found out that our method could improve the inpainting speed and ensure the matching accuracy at the same time.

3.2 Patch Inpainting

3.2.1 Propagation of Exemplars

When all priorities of the target region have been computed, we find the patch Ψp with highest priority. Then, we fill it with the source region φ which is the most similar to Ψp . The exemplar based propagation is conducted to recover the missing pixels in the selected patch Ψp . Several exemplar patches Ψqi are selected and missing pixels in Ψp are propagated by synthesizing corresponding pixels in Ψqi .

The exemplar patches are selected from the sum of squared difference (SSD) measure between Ψp and a patch Ψq in Ω as

SSD
$$(\Psi_{p}, \Psi_{q}) = \sum_{i=1}^{M} \mu_{i} (\Psi_{p}(i) - \Psi_{q}(i))^{2}$$

Where, $\Psi p(i)$ and $\Psi q(i)$ are the *i*th pixel value in respective patches. M is the size of the patch. μ_i is pixel mask function and defined as

$$\mu_{i} = \begin{cases} 1, if \Psi_{p}(i) \in (I - \Omega) \\ 0. If \psi_{p}(i) \in \Omega \end{cases}$$

3.2.2 Updating terms

When the patch ψ_p has been filled with pixel values of the source block, the relative confidence of patches on the fill front is change. We must update the confidence C (p). We restore the lost area by copying the known image in the corresponding position. However, the inpainting process would change some pixels' state, such as the original point on the boundary may become known pixel, the original point in Ω may become a new boundary point and so on. In order to do the inpainting in a correct order, it is necessary to update the boundary data, confidence information in time. Finally, the priority of the boundary in the target region will be updated.

4.IMPLEMENTATION AND EXPERIMENT RESULTS

In this section, we do some experiments to evaluate the performance of our proposed method. To validate the proposed image inpainting algorithm, the results are compared with some of the existing proposed frameworks [9] and [18].

Figure 3 and Figure 4 are classical images used in many image restoration research papers. Figure 5 is a natural image from the internet. The images in each figure are arranged as original image, an image with occluded region, the final result of methods in [9], [18] and our proposed algorithm respectively.

Fig. 3 Reconstruction of bird occluded region of image. (a) Original Image. (b) The target region has been blanked out. (8% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using Zhaolin Lu et al's algorithm. (e) Reconstructed image using proposed algorithm.



(e)

Fig. 4 Reconstruction of man occluded region of image. (a) Original Image. (b) The target region has been blanked out. (12% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using Zhaolin Lu et al's algorithm. (e) Reconstructed image using proposed algorithm.



(b)

(a)









Fig. 5 Reconstruction of lady occluded region of image. (a) Original Image. (b) The target region has been blanked out. (10% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al's algorithm. (d) Reconstructed image using Zhaolin Lu et al's algorithm. (e) Reconstructed image using proposed algorithm.

(**d**)





(e)

The best result of our implemented Criminisi method and Zhaolin Lu's method with 9 * 9 patch size is shown in Figure 3(c) and 4(d) respectively.

The corresponding PSNR of these results are 33.22dB and 34.79dB.

The results of our proposed method are shown in figures 3(e), 4(e) and 5(e). PSNR of these images are comparatively fair which are higher than the Criminisi's and Zhaolin Lu's result.

Table 1	PSNR value for the three exemplar based
	image inpainting Results

Image Method	Lady occluded image	Man occluded image	Bird occluded image
Criminisi et al's	33.12	33.16	33.22
Zhaolin Lu et al's	34.65	34.79	34.62
Proposed Method	44.34	45.67	44.58

Table 1 shows the implementation results of exemplar based inpainting methods proposed in [9],[18] and the proposed algorithm.

Our proposed method does not only overcome the Criminisi's method on PSNR but also on its visual appearance. A visual comparison between the proposed algorithm and the algorithms in [9] and [18] is presented in Figure3 – figure5. It can be seen that the images produced by proposed algorithm are comparably more perceivable. In terms of quantitative comparison the proposed framework has achieved a better peak signal to noise ratio (PSNR) in case of test images taken.

During the testing it was found that while some images could look visually pleasing, they may have extremely low PSNR values.

5.CONCLUSION

The existing image completion algorithms are time consuming, and the results are not satisfactory. The experimental results show its potential in comparison with the state of the art inpainting techniques. The major novelty of this work is that an improved patch priority term and an appropriate search region for best patch match are introduced into the exemplar based inpainting algorithm. It not only make the damaged area and the matching area match exactly, but also achieve to repair the image small spots, scratches and the large damaged region perfectly. The results of our proposed method have a noticeable improvement in visual quality from the exemplar-based conventional inpainting, both Criminisi's and Zhaolin Lu's method. While this paper addresses inpainting of still photographs, it can also be extended to inpainting of video frames.

6.REFERENCES

- M. Bertalmio, G. Sapiro, V. Caselles and C. Ballester, "Image inpainting," in Proceedings of ACM SIGGRAPH Conference on Computer Graphics, 2000, pp. 417-424.
- [2] M. Bertalmio, A. Bertozzi, G. Sapiro, Navier-Stokes, fluid dynamics, and image and video inpainting, Proceedings of the IEEE Computer Vision and Pattern Recognition (CVPR), Hawaii, 2001.
- [3] M. Bertalmio, L. Vese, G. Sapiro, and S. Osher, "Simultaneous structure and texture image inpainting", Proc. Conf. Comp. Vision Pattern Rec., Madison, WI, 2003.
- [4] T. Chan, J. Shen, Non-texture inpainting by Curvature-Driven Diffusions (CCD), J. Vis. Commun. Image Represent. 12 (2001) 436–449.
- [5] T.F. Chan, S.-H. Kang, J. Shen, Euler's elastica and curvature based inpainting, SIAM J. Appl. Math. 63 (2002) 564–592.
- [6] T.F. Chan, J. Shen, Mathematical models for local nontexture inpainting, SIAM J. Appl. Math. 62 (2002) 1019–1043.
- [7] T.F. Chan Sung Ha Kang, Error analysis for image inpainting, CAM 04-72, 2004
- [8] A. A. Efros and T. K. Leung, "Texture synthesis by non-parametric sampling," in Proc. IEEE ICCV, 1999, pp. 1033–1038.
- [9] 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.
- [10] A. Buades, B. Coll, and J.-M. M orel, "Image denoising by non-local averaging," in Proc. IEEE ICASSP, 2005, vol. 2, pp. 25–28.
- [11] K. Dabov, A. Foi, V. Katkovnik, and K. O. Egiazarian, "Image denoising by sparse 3-d transform-domain collaborative filtering.," IEEE Trans. Image Process., vol. 16, no. 8, pp. 2080–2095, Aug. 2007.
- [12] J. Yang, J. Wright, T. Huang, and Y. Ma, "Image super resolution as sparse representation of raw image patches," in Proc. IEEE CVPR, 2008, pp.1–8.

- [13] D. Glasner, S. Bagon, and M. Irani, "Superresolution from a single image," in Proc. IEEE ICCV, 2009, pp. 349–356.
- [14] Z. Xu and J. Sun, "Image inpainting by patch propagation using patch sparsity," IEEE Trans. Image Process., vol. 19, no. 5, pp. 1153–1165, May 2010.
- [15] A. Wong and J. Orchard, "A nonlocal-means approach to exemplar-based inpainting," in Proc. IEEE ICIP, 2008, pp. 2600–2603.
- [16] B. Shen, W. Hu, Y. Zhang, and Y.-J. Zhang, "Image inpainting via sparse representation," in Proc. IEEE ICASSP, 2009, pp. 697–700.
- [17] Y. Wexler, E. Shechtman, and M. Irani, "Spacetime completion of video," IEEE Trans. Pattern Anal. Mach. Intel., vol. 29, no. 3, pp. 463–476, Mar. 2007.
- [18] Zhaolin Lu, He Huang, Leida Li, Deqiang Cheng "A Novel Hybrid Image Inpainting Model" presented at the IEEE International

Conference on Genetic and Evolutionary Computing, 2010.

- [19] 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.
- [20] I. Drori, D. Cohen-Or, and H. Yeshurun, "Fragment-based image completion," ACM Trans. Graph, vol. 22, no. 2003, pp. 303–312, 2005
- [21] K. Sangeetha , P. Sengottuvelan , E. Balamurugan, "Improved Exemplar Based Texture Synthesis Method for Natural Scene Image Completion", International Journal of Computer Science Issues, Vol. 8, Issue 5, No 2, 2011,pp.283-287.
- [22] B. Wohlberg, "Inpainting with sparse linear combinations of exemplars," in Proc. IEEE ICASSP, 2009, pp. 689–692
- [23] K. Sangeetha, P. Sengottuvelan, E. Balamurugan, "A Comparative Analysis of Exemplar Based Image Inpainting Algorithms", European Journal of Scientific Research, Vol.60 No.3 ,2011, pp.316-325.