A Novel Exemplar-based Non-Local Algorithm for Image Inpainting

Guowei YANG[1, 2*] , Fan YANG[2,3], Xiaodong ZHUANG[1]

[1]*School of Electronic and Information Engineering*, Qingdao University, Qingdao 266071, China

[2]*School of Technology*, Nanjing Audit University, Nanjing 211815, China

[3] *School of Information Engineering*, Nanchang Hangkong University, Nanchang, 330063, China

***Abstract* — A novel exemplar-based image inpainting algorithm using the Non-Local Means (NLM) algorithm and Criminisi algorithm is proposed. In order to decrease the error in match rate, the new algorithm adopts the sum of squared differences (SSD) search method for several exemplars to generate a candidate exemplar set. Then it determines the Hausdorff distance as measurement criterion to find a match block by computing the weighted average of the exemplar set so that the image edge structure is preferentially propagated. Experimental results demonstrate that the improved algorithm keeps the image structure better and obtains better visual appearance.**

Key words - image inpainting; non-local means; emeplar-based; Criminisi algorithm; Hausdorff distance

I. INTRODUCTION

Image inpainting is one of the widely studied hot issue in the field of image processing and computer vision, it has been successfully applied in the ancient cultural relic protection and restoration, image coding, film special effects production and video image transmission, etc[1,2]. The purpose of it is to use undamaged area to fill or complement damaged area in the image, and evaluating the effect of visual images after inpainting from the perspective of people's subjective.

The present image inpainting technology is mainly divided into two categories: based on diffusion model method and based on texture synthesis method (exemplar-based method). Based on diffusion model method uses anisotropic partial differential equations and adopts propagation mechanism in pixels, so that the information of undamaged area spread to the damaged area. Bertalmio et al. first proposed a high order partial differential equation based on diffusion theory[3]. It’s basic idea is to use the information surrounding the damaged area, along the isophotes direction, make image information be gradually spread into the inpainting region to achieve the damaged area be filled. Chan et al. proposed using Total Variation model and its improved model that is also typical diffusion inpainting method[4], such as Curvature Driven Diffusion that is CDD method[5]. But in the practical application, when dealing with large inpainting region, the use of this kind of method is easy to cause the inpainting region fuzzy, influence inpainting results outline. Emeplar-based inpainting method can solve the fuzzy problem, the method based on image block as a unit, using the known image information block filling the damaged area. Bertalmio et al. decomposed the image is into two part structure and texture, respectively using the diffusion method and texture synthesis method[6], so as to obtain the final image. Drori et al. proposed fragment-based image completion[7], but its processing speed more slowly. Criminisi et al. proposed an exemplar-based inpainting approach[8] (Criminisi algorithm, to make it short). By searching the most similar target block to fill the inpainting domain to achieve the purpose of repair, it makes a good recovery effect. But it has problem that when select the inpainting priority pixel will lead to wrong filling order and select the best match block generates incorrect matches. Wong and Orchar proposed a nonlocal-means inpainting approach[9], but it without considering the filling sequence boundary and its matching criterion according to SSD by merely selecting 10 blocks to compute weighted average as match block value so that produced relatively large errors. Tang F et al. based on Criminisi algorithm, narrowed the exemplar region searching area[10], it had shorten the running time of the algorithm, but to a certain extent at the expense of repair quality. Sun J et al. firstly did manual inpainting on specified structure information, then used the texture synthesis method to pack breakage area, and improved the filling sequence [11]. Jing Wang et al. proposed robust object removal with an exemplar-based image inpainting approach, introducing the standard factor to adjust the priority of inpainting block, adopting SSD and NCC as matching criterion to search match block, but the idea is still looking for one best matching block to inpainting the damaged area[12].

In this paper, we propose an improved exemplar-based inpainting approach which based on the non-local means(NLM) algorithm and Criminisi algorithm that aiming at reducing the false matching rate. We first search the weight average value of matching blocks that have searched. We first adopt SSD as matching criterion searching for several exemplars to generate a candidate exemplar set. We then fill the damaged area with the weighted average value of exemplar through making use of Hausdorff distance as measurement criterion.

II. NL-MEANS ALGORITHM

Non-local means is widely used in the field of image denoising. The main idea is to use self-similarity of natural image, do image denoising by computing a weighted average of the relatively high similarity region.

Given a discrete noisy image $v(i)=\{v(i), i\in I\}$, with $i\in N_i$, $j\in N_i \Rightarrow i\in N_j$, the estimated value $NL[v](i)$ is computed as a weighted average of all the pixels in the image,

$$NL[v](i)=\sum_{j\in I} w(i,j)v(j) \quad (1)$$

For each pixel i in $v(N_i)$ the computation of the weight is based on the square of the Euclidean distance between patches $v(N_i)$ and $v(N_j)$, the Euclidean distance preserves the order of similarity between pixels,

$$d(i,j)=\left\|v(N_i)-v(N_j)\right\|_{2,a}^2 \quad (2)$$

the weights associated with the quadratic distances are defined by

$$w(i,j)=\frac{1}{Z(i)}\exp(-\frac{d(i,j)}{h^2}) \quad (3)$$

where $w(i,j)$ satisfy the usual conditions $0\le w(i,j)\le 1$ and $\sum_j w(i,j)=1$. $Z(i)=\sum_j \exp(-d(i,j)/h^2)$ is a normalization constant, h acts as a filtering parameter controlling the decay of the exponential function.

III. CRIMINISI ALGORITHM

Firgure 1 illustrates the model of Criminisi algorithm. The Original image is denoted with I, with the damaged region Ω, its contour $\partial\Omega$, and the source region Φ as exemplar region, i.e., without information loss region. p is one pixel point in $\partial\Omega$, and ψ_p centered on the point p is a inpainting patch, i.e., a target patch, its window size is 9×9 in [6]. n_p is the normal to the contour $\partial\Omega$ at point p, and $\nabla I_p^{\perp}$ is the isophote at point p.

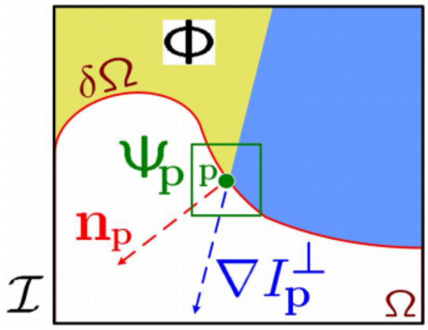


Figure 1. Criminisi algorithm model diagram

Criminisi algorithm is mainly implemented by three key steps. Firstly, computing patch ψ_p priority $P(p)$, it is defined as:

$$P(p)=C(p)D(p) \quad (4)$$

where $C(p)$ is the confidence term and $D(p)$ is data term. The higher the confidence term, the more known pixels the block unit area contains. The data term ensure that the image of linear structure can be priority inpainted. They are defined as follows:

$$C(p)=\frac{\sum_{q\in\psi_p\cap\Phi} C(q)}{\left|\psi_p\right|} \quad ; \quad D(p)=\frac{\left|\nabla I_p^{\perp}\bullet n_p\right|}{a} \quad (5)$$

where q is an arbitrary point in ψ_p.During initialization, $C(p)=1, \forall p\in\Phi$, $C(p)=0, \forall p\in\Omega$. a is a normalization factor (e.g., a = 255 for a typical grey-level image).

Secondly, find the optimal matching patch. To fix the most similar matching block by adopting global search method and using the sum of squared differences(SSD) as matching criterion. The damaged blocks corresponding defect pixel being filled, propagating texture and structure information. Search in the source region for that patch which is most similar to ψ_p denoted as $\psi_{\hat{q}}$ can be defined as follows:

$$\psi_{\hat{q}} = \arg\min d(\psi_p, \psi_q), \quad \psi_q \in \Phi \tag{6}$$

Finally, update confidence values and contour.

IV. THE NOVEL EXEMPLAR-BASED NON-LOCAL ALGORITHM

Digital images contains a lot of redundant information, sometimes there are multiple exemplar patches have the same SSD distance with the inpainting patch, Criminisi algorithm select the optimal matching patch randomly. When the optimal matching patch is selected inappropriate, it's easy to cause the error accumulation so as to reduce the repair quality. And measuring solely on the SSD as the matching degree, considered only the RGB values similarity between the pixel patches without taking into account the structure and edge information difference. In this paper, we propose that use multiple similar exemplar patch weighted average to estimate the inpainting patch, to improve the similarity between instead of patch and inpainting patch, make the transition more natural. And based on SSD adopt Hausdorff distance assigned weight contribution value to exemplar patch with the similar SSD distance, so that structure region pixels have a higher weight.

For searching for a matching patch of a target patch ψ_p that centered on the point p, firstly, we select a $W \times W$ size area as search window, and we find m patches that almost have minimum SSD distance with ψ_p in the search window area. Then, we get the weighted average value of the m patches.

Each selected exemplar patch ψ_i, its weight model is :

$$\omega(\psi_p, \psi_i) = \exp\left(-\frac{H(\psi_p, \psi_i)}{K_i h} \right) \tag{7}$$

where $K_i = count(\Omega_i / (2N+1)^2)$ is the effective area ratio, i.e. ψ_i and ψ_p corresponding to known points accounted for the proportion of $(2N+1)^2$. h is a weight decay parameters. $H(\psi_p, \psi_i)$ is Hausdorff distance, it is commonly used in image matching field for calculate the matching degree between two point sets. It can be defined as follows:

$$H(\psi_p, \psi_i) = \max\{h(\psi_p, \psi_i), h(\psi_i, \psi_p)\} \tag{8}$$

where ： $h(\psi_p, \psi_i) = \max_{a \in \psi_p} \min_{b \in \psi_i} \|a - b\|$, $h(\psi_i, \psi_p) = \max_{b \in \psi_i} \min_{a \in \psi_{p_i}} \|b - a\|$ 。

The matching block that is used to fill the inpainting block ψ_p denoted as $\psi_{\hat{p}}$, it can be defined as follows:

$$\psi_{\hat{p}} = \frac{1}{Z(i)} \sum_{i=1}^{m} \omega(\psi_p, \psi_i) \psi_i \tag{9}$$

where $Z(i) = \sum_{i=1}^{m} \exp(-H(\psi_p, \psi_i) / K_i h)$ is a normalization constant.

To sum up, the implementation steps of this algorithm are as follows:

(1)Determine the inpainting region Ω and its contour $\partial\Omega^t$, if $\partial\Omega^t$ is null, then exit.

(2)According to the formula (4), compute the priority $P(p)$ of the point p that on the contour $\partial\Omega^t$.

(3)Find target region $\psi_{\hat{p}}$ that size is $(2N+1)(2N+1)$ and have maximum priority, i.e. $\psi_{\hat{p}} \mid \hat{p} = \arg\max_{p \in \partial\Omega^t} P(p)$.

(4)Selecting a $W \times W$ size area centered on the point $\hat{p}$ as searching window, calculate the Euclidean distance between $\psi_{\hat{p}}$ and $\psi_{\hat{q}}$, find m patches that almost have minimum SSD distance with $\psi_{\hat{p}}$ as exemplar sets.

(5)According to the formula (9), calculate the similarity weight value between each exemplar patch and $\psi_{\hat{p}}$, and compute its weighted average value as the matching patch ψ'_p.

(6)Filling the unknown pixels image information in $\psi_{\hat{p}}$ with the corresponding information in ψ'_p.

(7)Updating $C(p), \forall p \in \Psi_{\hat{p}} \cap \Omega$.

(8)Repeating steps (1)~(7) until the inpainting region Ω is null, the process to be over.

The whole design flow chart, see Figure 2.

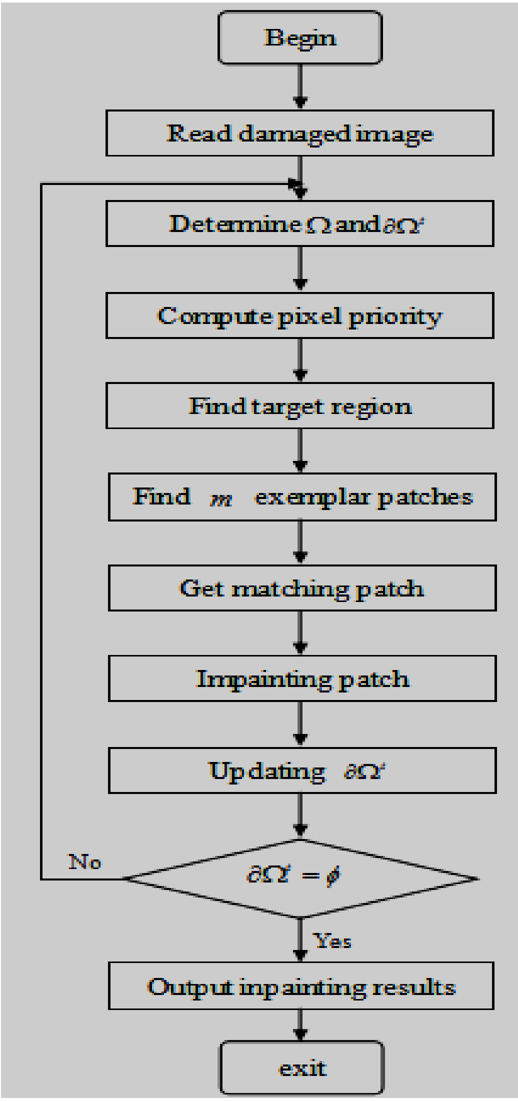


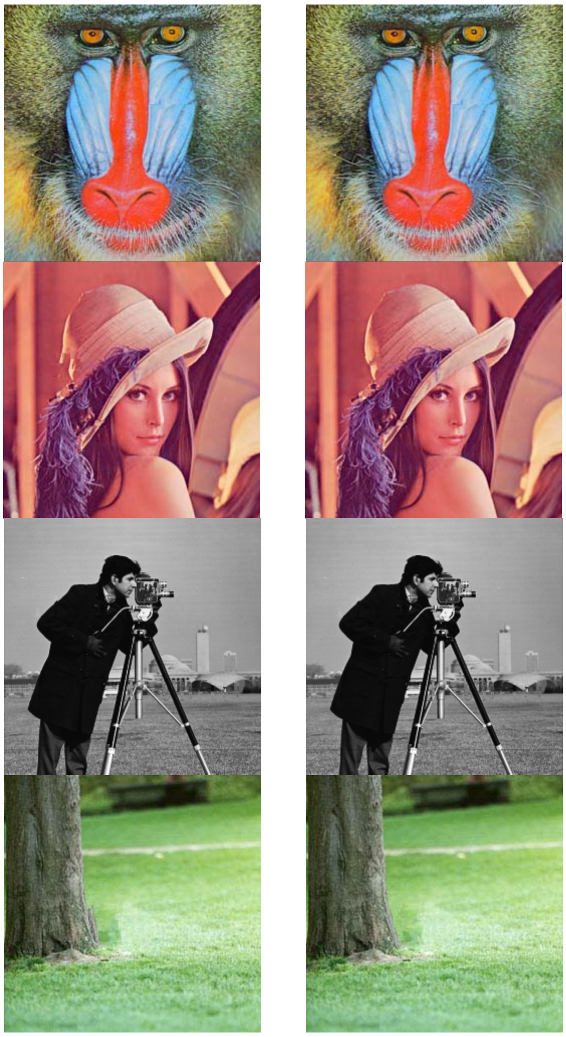
Figure 2. Flow chat of algorithm.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In order to verify the feasibility the effectiveness of the inpainting algorithm proposed in this paper, we use VS2008 software tool combined with OpenCV programming to compare image inapinting effects between our algorithm and Criminisi algorithm. In the experiment, the inpainting patch size and the exemplar patch size are all set to 9×9, and the search window size is set to 41×41. Weight decay parameters h is set to $4\delta^2$, δ^2 is the variance of inpainting patch. Our experimental images size are all 256×256. In this paper, we mainly uses the subjective evaluation method, through the subjective observation to measure the inpainting effect. The experiment results are represented in figure 3 below.

(a) Criminisi algorithm

(b) our algorithm



(c) (d)

Figure 3. Inpainting results comparison

From the results figure, our algorithm can obtain better image inpainting effects in details, text removal and object removal. Compared with Criminisi algorithm, our algorithm first ensure the reasonable filling the edge structure information, so that it have better effect in structure region of the image, exemplar block error matching rate are decreased, and the final image are more vulnerable to human visual satisfaction.

VI. CONCLUSIONS

This paper presented an image inpainting algorithm which based on NLM algorithm and Criminisi algorithm. Due to the introduction of non-local concept and Hausdorff distance, the inpainting effect has been greatly improved. Our algorithm mainly through the method of obtaining selected exemplar sets weighted average can effectively improve the block matching rate. Experimental results show that the algorithm has improved repair effect compared with Criminisi algorithms, especially has obvious advantages in inpainting edge structure region of image.

ACKNOWLEDGMENTS

This program is financially supported by the Natural Science Foundation of China (No.61272077) and Program of Jiangxi Province Science and Technology (20133BB E50022).

REFERENCES

[1] S. M. Muddala, M. Sjöström and R. Olsson, "Virtual view synthesis using layered depth image generation and depth-based inpainting for filling disocclusions and translucent disocclusions," Journal of Visual Communication and Image Representation, vol.38, pp.351-366, 2016.

[2] T. Barbu, "Variational image inpainting technique based on nonlinear second-order diffusions," Computers & Electrical Engineering, In Press, Corrected Proof, Available online, vol.23, 2016 .

[3] M. Bertalmio, G. Sapiro, V. Gaselles, et al., "Image inpainting," Proceedings of the 27th Annual Conference on Computer raphics, New York:ACM, pp.417 – 424, 2000.

[4] T. F. Chan and J. H. Shen. "Mathematical models for local non-texture inpainting," SIAM Journal of Applied Mathematics, vol.62, pp.1019-1043, 2001.

[5] T. F. Chan and J. H. Shen, "Non-texture inpainting by curvature-driven diffusions," Journal of Visual Communication and Image Representation, vol.12, 436-449, 2001.

[6] M. Bertalmio, L. Vese, G. Sapiro, et al., "Simultaneous structure and texture image inpainting," IEEE Transactions on Image Processing, vol.12 , pp.18-20, 2003.

[7] I. Drori, D. Cohenor, H. and Yeshurun, "Fragment-based image completion," ACM Transactions on Graphics, vol.22, 303-312, 2003.

[8] A. Criminisi, P. Perez and K. Toyama, "Region filling and object removal by exemplar-based inpainting," IEEE Computer Transactions on Image Processing, vol.13, 1200-1212, 2004.

[9] A. Wong and J. Orchard, "A nonlocal-means approach to exemplar-based inpainting," In ICIP, San Diego, pp.2600-2603, 2008.

[10] F. Tang, Y. T. Ying, Wang J, et al., "A novel texture synthesis based algorithm for object removal in photographs," Proceedings of 9th Asian Computing Science Conference, Chiang Mai, Thailand, pp.248-258, 2004.

[11] Sun J, Yuan L, Jia J Y, et al., "Image completion with structure propagation. ACM Trans on Graphics," vol.24, pp.861-868, 2005.

[12] Wang J, Lu K, Pan D, et al., "Letters: Robust object removal with an exemplar-based image inpainting approach," Neurocomputing, vol.123, 150-155, 2014.