IJCES International Journal of Computer Engineering Science , Volume2 Issue 1 ISSN : 2250:3439
https://sites.google.com/site/ijcesjournal http://www.ijces.com/

The Proposal of a New Image Inpainting Algorithm

Ouafek Naouel[1], M. Khiredinne Kholladi [2],

[1] Department of mathematics and computer sciences
ENS Constantine, MISC laboratory
Constantine, Algeria
naouelouafek@yahoo.fr

[2] Department of computer sciences
Mentouri Constantine, MISC Laboratory
Constantine, Algeria
kholladi@yahoo.fr

Abstract. In the domain of image inpainting or retouching, many recent works focus on combining methods of different fields of research in order to obtain more accurate results, and more original images. In this paper we propose a new algorithm that combines three different methods, each one represent a separate field. The first one for the use of artificial intelligence, the second one for the use of the partial differential equation (PDE) and the last one for the use of texture synthesis to reconstruct damages images.

Keywords: Inpainting; retouching; isophotes; texture synthesis; PDE; Digital image.

1 Introduction

The reconstruction of damaged images (also known as inpainting or retouching) was performed a long time ago by professional artists and now it becomes an issue of great interest in image processing which aims to automate the process and do it in a minimum of time. The restoration of the missing fragments of old manuscripts allows us to safeguard the national heritage. Other new objectives appeared such as: remove a title, or paragraphs from an image, or even in special effects: add or remove elements from the original image.

This paper is organized as follows: In the next section we introduce different techniques proposed in the literature for the reconstruction of damaged pictures later in the section three we present our contribution. In section four we present the application and the last section we conclude this work.

2 Related works

Many works have recently introduce the digital image inpainting algorithms. Firstly Bertalmio et al [1] proposed a new digital algorithm based on filling the corrupted area by propagating information from the outside along isophotes (lines of equal gray value) direction. The user provide a mask border the inpainting area and the isophotes directions are calculated by the discretized gradient vector that gives the direction of largest spatial change, and the information to be propagated along the isophotes direction is obtained by a smooth way of the line arriving at the gap boundary, to calculate this they used a simple discrete implementation of the Laplacian. The algorithm runs alternatively with same steps of anisotropic diffusion [11] in order to preserve boundaries in the reconstruction.

Oliveira et al [2] proposed a simple and faster image inpainting algorithm that uses Gauss convolution kernel.

Uhlir et al [3] used Radial Basis Functions (RBF) for reconstruction of damaged images and for eliminating noises from corrupted images.

Chan et al [4] proposed the Total Variational (TV) inpainting model uses an Euler-Lagrange equation and inside the inpainting domain the model simply employs anisotropic diffusion based on the contrast of the isophotes.

This type of algorithms, is used for inpainting small gaps, other recent works can fill large gaps using the technique "Texture syntheses".

Criminisi et al [5] proposed an exemplar based inpainting method, which fills in the target region with patches from the source region possessing similar texture. The candidate patches are selected from the whole image with special priority to those along the isophotes (lines of equal gray value) so as to preserve the linear structure during the filling-in. This process is quite similar to patch matching in texture synthesis and the fill-in priority is inspired by the partial differential equations method of physical heat flow [6].

Inspired by the work of Criminisi et al, Tang et al [6] proposed a novel texture synthesis method called coherence-based local searching (CBLS) for region filling, this method minimize the researching area of patches in the neighbor regions which can provide sufficient information to decide what to fill, instead researching in the whole source regions.

Ashikhmin et al [10] proposed an algorithm for structure synthesis, its limit is that it needs a texture model to run; to use this algorithm you must provide a texture model.

At the present works recent works focus on the use of artificial intelligence in the inpainting process in order to obtain more precise retouching.

Elango et al [7] proposed a novel algorithm based on a cellular neural network. In a very recent work (2011) Masnou et al [8] proposed a new algorithm based on K-nearest neighbor algorithm.

IJCES International Journal of Computer Engineering Science ,
Volume2 Issue 1 ISSN : 2250:3439
https://sites.google.com/site/ijcesjournal http://www.ijces.com/

3 Our algorithm

In our algorithm we tried to combine the advantages of these approaches, with use artificial intelligence.

The algorithm contains three major steps (Fig 1.). The objective of the first one is to segment the original image in order to separate each texture alone; at the end of this step we transform the original image in a gray-valued image.

This image will be the input of the second step which aims at connecting every point $\mathbf{P_i}$ with $\mathbf{P_j}$ in the boundary of the region $\mathbf{\Omega}$ to be inpainted.

Note that **P** is the point when two textures ($\mathbf{T_1}$ and $\mathbf{T_2}$) and the boundary $\partial\mathbf{\Omega}$ cross each other (Fig 2.)

The third step consists in the process of filling the area $\mathbf{\Omega}$ with the appropriate texture.

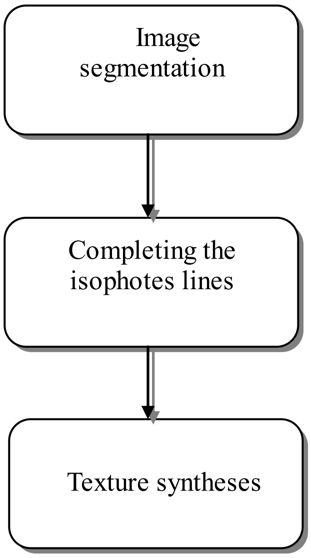

Fig.1. The 3 big steps of our algorithm.

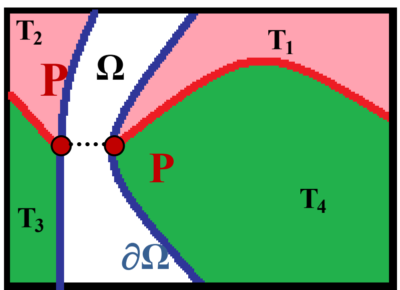

Fig. 2. Description of the point P.

The three steps are detailed below:

Image Segmention:

In this step we use the artificial intelligence K-means algorithm to divide the original image in to a group of regions, each region containing a different structure.

Completing the Isophotes Lines:

In this step we use the works of Masnou and Morel [9] that generalizes the principle of extrapolates broken edges using elastica-type curves to the isophotes of a gray-valued image.

The principle consist in the following: let $L_1$and L_2 be two lines arising at the boundary of the inpainting area. $L_1$and L_2 can be connected only if they have the same level and the same orientation. Since level lines can never cross, a global disocclusion will be valid if and only if this condition is satisfied see (Fig 3.) [9].

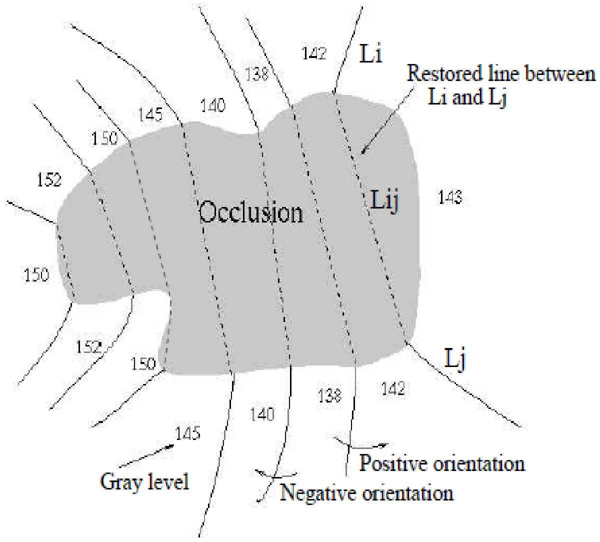

Fig.3. An occlusion and possible connection of level lines tow by tow [9] images taken from their paper.

Texture Synthesis:

In this step we fill the region $\mathbf{\Omega}$ by textures that surrounding the boundary $\partial\mathbf{\Omega}$ as follows:

Firstly, the region $\mathbf{\Omega}$ to be inpainted is devided into $\mathbf{\Omega_i}$ in the same number of texture that border it (result of the second step of our algorithm).

Secondly, for each $\mathbf{\Omega_i}$:

If the texture T_1 that border $\mathbf{\Omega_i}$ in right is the same texture T_2 in his left then fill the gap $\mathbf{\Omega_i}$ with one of them (Fig 4.).

Else divide the region $\mathbf{\Omega_i}$ in two parts in the middle then fill its right and left sides with the texture that borders it in the same side (Fig 5.).

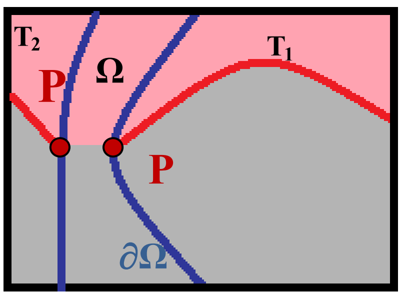

Fig.4. $T_1 = T_2$

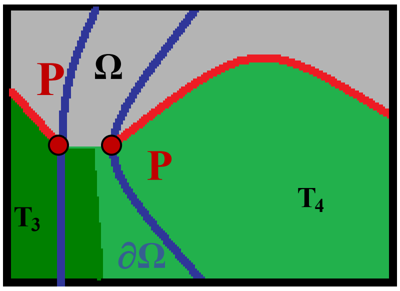

Fig.5. $T_3 \neq T_4$

4 Application

Actually, we work on this phase; we use to implement this algorithm the JAVA language, and such environment Eclipse

5 Conclusion

In this paper, we have proposed a new algorithm that combines three different methods; the first one is K-means classifier to determine texture around the gap. The second method is to curve isophotes to relate each connection point, and the third one to fill the gap with the appropriate texture.

In future works we will determine the details of the implementation, and shows the results obtained by our algorithm.

References

1. Bertalmio, M., Sapiro, G., Caselles, V., Ballester, C.: Image Inpainting. In: Proceeding of SIGGRAPH pp. 417-424, (2000)
2. Oliveira, M., Bowen, B., McKenna, R., and Chang, Y-S.: Fast Digital Image Inpainting. In: Proceedings of the Visualization, Imaging, and Image Processing IASTED Conference, Marbella, Spain, 261-266, Sept. (2001)

3. Uhlír, K., Skala, V.: Reconstruction of damaged images using radial basis functions. In: Proceedings of EUSIPCO 2005 p. 160,Bogazici University, 34342, Bebek, Istanbul, Turkey, (2005),
4. Chan, T.F., Shen, J.: Mathematical models for local deterministic inpaintings.: In: SIAM Journal of Applied Math., (2001)
5. Criminisi, A., Perez, P.,Toyama , K.: Object Removal by Exemplar-Based Inpainting. In: CVPR, Madison, Wisconsin, June, (2003)
6. Tang, F., Ying, Y., Wang, J., Peng Q.: A Novel Texture Synthesis Based Algorithm for Object Removal in Photographs. In: M. J. Maher (Ed.): ASIAN 2004, LNCS 3321, pp. 248–258, 2004. © Springer-Verlag Berlin Heidelberg (2004)
8. Elango, P., Murugesan, K.: Digital Image Inpainting Using Cellular Neural Network. In: Int J. Open Problems Compt. Math., Vol. 2, No. 3, September 2009 ISSN 1998-6262; Copyright ©ICSRS Publication, (2009)
9. Le Meur, O., Gautier, J.: Examplar-based inpainting based on local geometry, In: Proceding of IEEE international conference on image processing, ICIP September-11-14, (2011)
10. Masnou, S., Morel, J.-M.: Level lines based disocclusion. In: 5th IEEE International Confrence on Image Processing, Chicago, Illinois, October 4-7, (1998)
11. Ashikhmin, M.: Synthesizing natural textures. In: The Proceeding of 2001 ACM Symposium on Interactive 3D Graphics, ACM Press, (2001)
12. Perona, P., Malik, J.: Scale-space and edge detection using anisotropic diffusion. In: IEEE-PAMI 12, pp. 629-639, (1990)