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A structure first Image Inpainting Approach Based on Self-Organizing Map (SOM)

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Abstract—This paper presents a structure first image inpainting method based on self-organizing map (SOM). SOM is employed to find the useful structure information of the damaged image. The useful structure information which includes relevant edges of the image is used to simulate the structure information of the lost or damaged area in the image. The structure information is described by distinct or indistinct curves in an image in this paper. The obtained target curves separate the damaged area of the image into several parts. As soon as each part of the damaged image is restored respectively, the damaged image is inpainted. The efficiency of the proposed method is demonstrated by the simulation results.

Keywords- image inpainting, curve fitting, neural networks, self-organizing map (SOM).

I. INTRODUCTION

Aging effects, bad maintenance, wearing or tearing and other problems can cause the deterioration or destruction of images or pictures. These partly damaged images or pictures can be inpainted by professional painters. With the rapid development of modern signal processing and computer-vision technology, many researchers have attempted to study suitable methods and algorithms to restore images from their partly damaged versions by using computers [1].

Image inpainting is first presented by Bertalmio, Sapiro, Caselles and Bellester[2]. Bertalmio et al. invented a successful digital inpainting scheme based on higher order Partial Differential Equations (PDE). There is a significant amount of research done on digital inpainting methods, which includes PDE scheme, Curvature Driven Diffusions (CDD) scheme, and Total Variation (TV) model [3-4]. Most of the current methods are following Bertalmio's idea, and estimates curvature of the isophotes [3-4]. These image inpainting techniques fill holes in images by propagating linear structures into the target region via diffusion. PDE scheme takes advantage of Thermo diffusion equation to diffuse the information of the regions around the damaged regions. Their drawback is that the diffusion process introduces some blur, which becomes noticeable when filling larger regions [5].

Due to the Neural networks' ability of solving nonlinear

problems, it has been applied in many research fields [6], [7]. Our previous work proposed a multilayer image inpainting method by using neural networks, and obtained good primary results [8].

Our last successful attempt of using SOM on image inpainting [8] has established the foundation for this research work.

Finding the structure information is the most important process in this structure first image inpainting method. In this paper, the structure information is described by distinct or indistinct curves in an image. Those curves can be linear or nonlinear. A curve always has a global trend such as ascending or descending, concave or convex. In this paper, the curve information in the damaged part of the image is calculated first. The damaged area is then divided into several parts by using the obtained curves. The final inpainted image will be obtained by inpainting each part of the damaged image.

The rest of the paper is organized as follows. Section 2 describes the layout of the proposed method. Section 3 shows the detailed process of inpainting and presents the experimental results. Finally Section 4 concludes the work.

II. LAYEROUT OF THE METHOD

Fig.1 shows the procedure layout of the proposed method. Structure searching is the first step of the proposed method, and the useful curves in the source image which contain relevant edges of the damaged parts are obtained. Unlike our previous work, in which SOM is employed to separate an image into several layers [8], SOM in this paper is used to learn the topology of the image structure, and simulates the curves which is relevant to the lost or damaged area of the damaged image. The curves which are obtained in the second step divide the damage area into several parts. After each part of the damaged image is restored respectively, the final inpainted image is obtained.

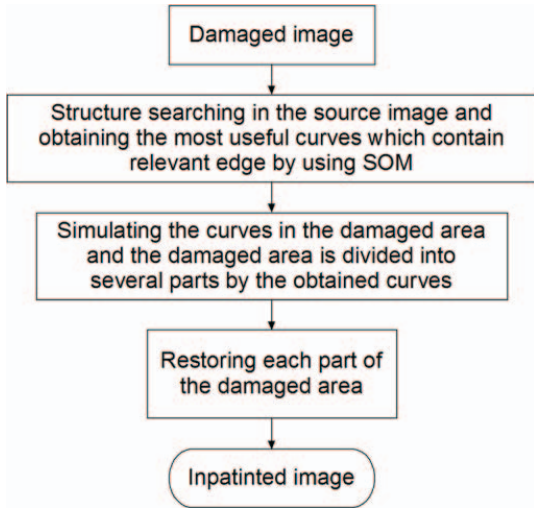


Figure 1 Flowchart of the proposed method

III. PROCESS OF THE INAPAINING METHOD AND EXPERIMENTAL RESULTS

A. Structure searching in the source area by using SOM

Self-organizing map (SOM) [9]-[10], which is also called Kohonen model, is proposed by Kohonen in 1982. It has been broadly applied in many research areas [8] [9] [10].

The algorithm process of SOM is shown in Fig.2, which was detailed in [8] [9] [10].

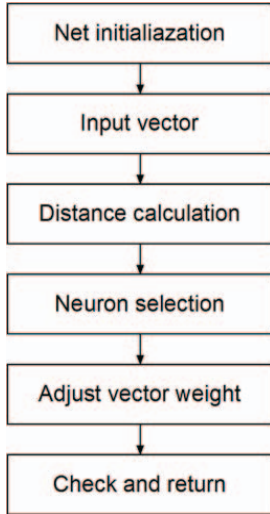


Figure 2 Flowchart of SOM algorithm

The distance is calculated by the following equation:

$$d_j = \sqrt{\sum_{i=1}^n (x_i - w_{ij})^2} \quad (1)$$

The weight vector of the neuron $w_i \in R^n$ is updated according to the following equations:

$$w_i(t+1) = w_i(t) + \eta(t)\Omega_{c(x)}(i,t)[x(t) - w_i(t)] \quad (2)$$

$$\|x - w_{c(x)}\| = \min_i \|x - w_i\| \quad (3)$$

$$\Omega_{c(x)}(i,t) = \exp\left(-\frac{\|p_i - p_{c(x)}\|^2}{2\sigma^2(t)}\right) \quad (4)$$

where t is the index of the regression step and the regression is performed for each presentation of a sample of $x \in R^n$, denoted $x(t)$. The scalar multiplier $\Omega_{c(x)}(i,t)$ is called the neighborhood function. Its first subscript $c(x)$ is the winning neuron whose weight vector is defined by (3) as $w_{c(x)}$. It matches best with x . Another scalar multiplier $\eta(t)$ is the learning-rate factor which decreases monotonically with the regression steps. The comparison metric is usually selected as Euclidean. The neighborhood function is often taken as Gaussian, which is defined by (4), where $p_i \in R^n$ and $p_{c(x)} \in R^n$ are the vectorial locations on the grid, and $\sigma(t)$ corresponds to the width of the neighborhood, which is also decreasing monotonically with the regression steps.

In this paper we pay attention to deal with the damaged areas with only one lost edge curve. We defined the edge curve that passes through the damaged area as relevant curve. Firstly all edges of the input image will be founded, and then other useless edges are removed except the relevant curve.

The image example is shown in Fig.3 (a), and the damaged area is defined as pure black.

A part of input image as target part which contains the damaged area as shown in Fig.3 (b) is selected, and the area is a little bigger than the damaged area for the pixels around the damaged area have the most relativity.

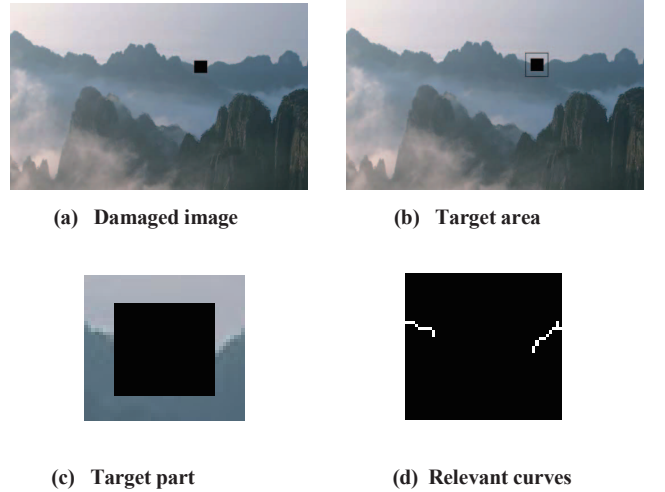
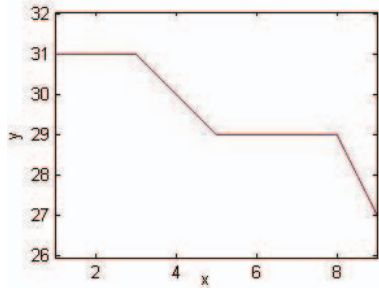


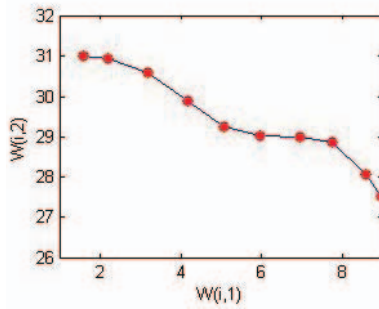
Figure 3 Process of relevant curves searching

In the next step the relevant curves which are shown in Fig.3 (d) will be analyzed by SOM. In Fig.3 (d) the white line is the structure information and also the input vector of the SOMs. SOM can simulate the structure and find out the

regularity of the line. The regularity can be described as a global trend. There are two relevant curves therefore we need to set up two SOM networks: SOM 1 and SOM 2. Each SOM simulates one line's structure. The neuron's number (N) of each SOM is equal to the pixel's number (P) of each relevant curve. The training results of the two SOMs are shown in Fig.4 and Fig.5. The output curves show the global trend of the relevant edge.

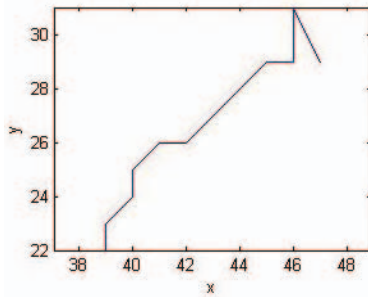


(a) Left relevant curve

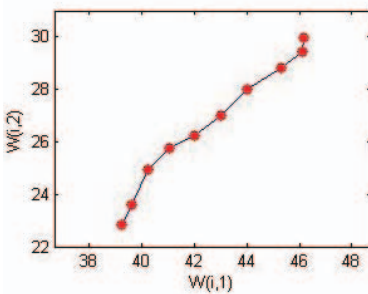


(b) Vector weight of SOM 1 after training

Figure 4 Inputs and outputs of SOM 1



(a) Right relevant curve



(b) Vector weight of SOM 2 after training

Figure 5 Inputs and outputs of SOM 2

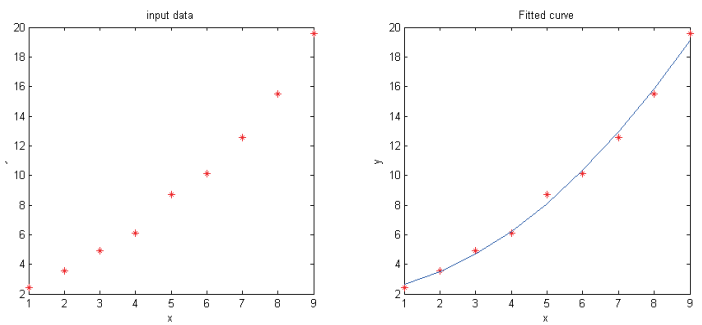
B. Simulating the curves in the damaged area and the experiment results

After the global trend that is the most important information of the whole process is found, we can use it to obtain the lost edge.

Polynomial fitting is an effective approach to fit curves. An example is shown in Table 1. By using polynomial fitting, a curve that can pass through all points smoothly is obtained as shown in Fig.6 (b).

Table 1 Several disperse points

variable	value								
x	1	2	3	4	5	6	7	8	9
y	2.45	3.56	4.89	6.13	8.69	10.12	12.56	15.48	19.57

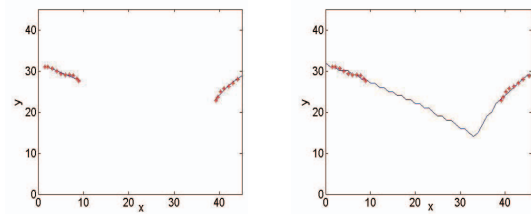


(a) Disperse points

(b) Fitted line by polynomial fitting

Figure 6 Polynomial fitting

In our case, the two output curves are linked by using the polynomial fitting method in the damaged area. It can produce a curve, which divided the damaged image into two parts as shown in Fig. 7 (b).



(a) Simulated line

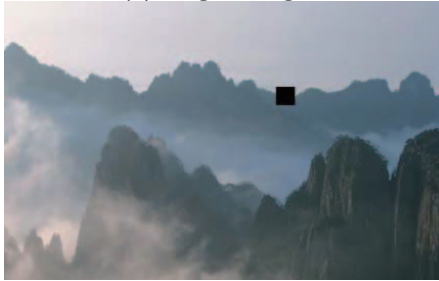
(b) Fitted line

Figure 7 Fitted lines by proposed method

After each damaged part has been inpainted, we get the final inpainting result. The process and final inpainted results are shown in Fig.8.



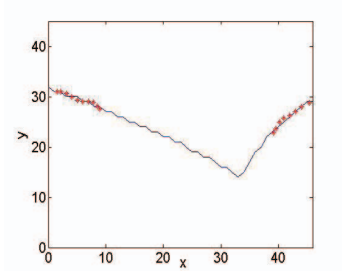
(a) Original image



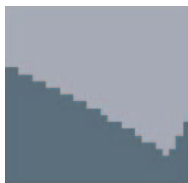
(b) Damaged image



(c) Target part



(d) Fitted edge



(e) Fitted damaged area



(f) Inpainted image

Figure 8 Process and result of the proposed method

From the above analysis, we can see that the approach proposed in this paper can restore the image effectively.

IV. CONCLUSIONS

Deterioration or damage of images can be caused by many matters and more and more researchers have been engaged in the research of image inpainting or image completing. The damaged area can be any shape with complicated structure information, and restoring the structure information of the damaged area is very important. Therefore, this paper proposes a structure first image inpainting method, which employs SOM to learn the structure information of the damaged image. This simple case is used to test the proposed method, and obtains good results. Extending the proposed method to more complicated applications is our future works to be done.

REFERENCES

- [1] A. P. A. de Castro, J. D. S. da Silva, "Restoring Images with a Multiscale Neural Network Based Technique", Proceedings of the 2008 International Joint Conference on Neural Networks, 2008, pp. 3197-3203.
- [2] M. Bertalmio, G. Sapiro, V. Caselles, and C. Ballester. "Image inpainting." in Proceedings of the 27th annual conference on Computer graphics and interactive techniques. ACM Press/Addison-Wesley Publishing Co. New York, USA, 2000, pp. 417-424.
- [3] H.-Y. Zhang, Q.-C. Peng, "A Survey on Digital Image Inpainting", Journal of Image and Graphics, vol.12, No.1, 2007, pp. 1-10 (in Chinese).
- [4] T. F. Chan, J. Shen, "Mathematical Models for Local Non-Texture Inpaintings", SIAM: Journal on Applied Mathematics, vol. 62, No. 3, 2001, pp. 1019-1043.
- [5] A. Criminisi, P. Perez and K. Toyama, Microsoft Research, "Region Filling and Object Removal by Exemplar-Based Image Inpainting", IEEE Transactions on image processing, September 2004, vol. 13, No. 9, pp.1200-1212.
- [6] A. P. Sangole, A. Leontitsis, "Spherical self-organizing feature map: An introductory review", International Journal of Bifurcation and Chaos, November 2006, vol.16, No.11, pp. 3195-3206.
- [7] Z. Wang, Y. Sun, Z.-Y. Wang, and et al, "The Research on Predicting Network Traffic Using Neural Networks", Journal of Optoelectronics laser, 2006, vol. 17, No. 10, pp. 1256-1258.
- [8] Q. Wang, Z. Wang, C.S.Chang, T. Yang, "Multilayer Image Inpainting Approach Based on Neural Networks", Fifth International Conference on Natural Computation, 2009, pp. 459-462.
- [9] T. Kohonen. "Self-organized formation of topologically correct feature maps", Biological Cybernetics, January 1982, vol.43, No.1, pp.59-69.
- [10] T. Kohonen. Self-Organization and Associative Memory, 2nd Edition, Berlin: Springer-Verlag, 1987.