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Multilayer Image Inpainting Approach Based on Neural Networks

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Abstract—**This paper describes an image inpainting approach based on the self-organizing map for dividing an image into several layers, assigning each damaged pixel to one layer, and then restoring these damaged pixels by the information of their respective layer. These inpainted layers are then fused together to provide the final inpainting results. This approach takes advantage of the neural network's ability of imitating human's brain to separate objects of an image into different layers for inpainting. The approach is promising as clearly demonstrated by the results in this paper.**

Keywords-image inpainting; layer separation; neural networks; SOM

I. Introduction

Deteriorations of images and pictures are often caused by aging effects, bad maintenance and other wearing or tearing problems. Partly damaged pictures can be inpainted by human painters. With the rapid development of modern processing and computer-vision technology, it is now feasible to develop digital techniques for performing the same task.. Many researchers have attempted to find suitable methods and algorithms to efficiently restore images from their partly damaged versions by computers automatically [1]. Automatic digital inpainting is a technique which restores damaged image or video by means of image interpolation [2]. The technique not only can inpaint damaged pictures, but can also be used in removing a user-selected region or object [2]. Image zooming can also take advantage of this technique.

inpainting is based on Partial Differential Equations (PDE) and calculus of variations [2]. This kind of approaches takes advantage of the Thermodiffusion equation to diffuse the information of the regions around the damaged regions to the damaged regions [3]. The most representative scheme of this kind of approaches is Curvature Driven Diffusions (CDD) scheme, whose conductivity coefficient depends on the curvature of the isophotes [4]. The CDD inpainting scheme cannot be lifted to a variation or Bayesian model, unless another new term representing the transportation mechanism is incorporated [2]. Besides, there is a variation inpainting technique based on Geometric image model, whose main idea is imitating the process of human artist inpainting. The most representative model of the technique is Total Variation (TV) model, which works remarkably well for local inpainting such as text removal [4, 5]. The major drawback of the TV inpainting model is that it does not restore a single object satisfactorily when the disconnected remaining parts are separated far apart by the inpainting domain [6].

The most recent approach to non-texture This paper is motivated to develop a novel neural network structure, employ it on the research of the images inpainting, and compare it with existing methods. The self-organizing map (SOM) is a fascinating neural network method that was originally proposed by Kohonen in 1982. It has received great attention from researchers in a variety of areas such as engineering sciences, medicine, biology and economics, and has found increasing applications in those fields [7].However, there is only a limited number of publications on the application of SOM on inpainting images has been reported. According to the ability of the SOM to visualize complex high-dimensional data by encapsulating physical measures of the data using unsupervised learning method, a novel inpainting images method based on SOM has been proposed in this paper. The proposed method can separate objects of an image into several layers, assign each damaged pixel to one layer by an assigning strategy, restore damaged pixels of each layer, combine the results of former process, and give the final inpainting results of the image. Compared with other method, such as the most representative TV model, the simulation results demonstrate that the inpainting method based on SOM not only is feasible, but is superior to the other method.

The rest of this paper is organized as follows. Section 2 describes the SOM and how does it separate an image into several layers. Section 3 describes in detail the proposed inpainting method. Section 4 presents the experimental results and analysis. Finally, Section 5 concludes the work.

II. Self-Organizing Map

Self-organizing [8] in networks is one of the most fascinating topics in the neural network field. Such networks can unsupervised learn to detect regularities and correlations in their input and adapt their future responses to that input accordingly. Self-organizing maps [9] learn to recognize groups of similar input vectors in such a way that neurons physically near each other in the neuron layer respond to similar input vectors. It consists of a finite set of models are associated with neurons that are arranged as a regular grid. The models are produced by a learning process that automatically orders them on the grid along with their mutual similarity. SOM differ from competitive layers in that neighboring neurons in the self-organizing map learn to recognize neighboring sections of the input space. Thus, self-organizing maps learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on.

The SOM algorithm is a recursive regression process, in which, the weight vector of ith neuron $w_i \in R^n$ is updated as

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

$$\left\| x - w_{c(x)} \right\| = \min_i \left\| x - w_i \right\| \quad (2)$$

$$\Omega_{c(x)}(i,t) = \exp\left(\frac{-\left\| p_i - p_{c(x)} \right\|^2}{2\sigma^2(t)}\right) \quad (3)$$

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 (2) as $w_{c(x)}$ 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 the Gaussian, which is defined by (3), 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.

From above algorithm we can learn that SOM can make input patterns cluster online, and each neuron’s input weight vector is the center of the corresponding cluster. In this paper, the input data of the SOM is composed by all pixels’ color of an image. The SOM approximately separates objects into different layers automatically through classifying the input colors.

III. INPAINTING STRATEGY

Most inpainting algorithms use the damaged image as a single layer, and computes the inpaint data based on the single layer. The approach may use irrelevant information on restoring an object, without considering the separation of the objects [2].

Considering human artist inpainting process, we can find that he usually inpaint the damaged parts of a object in the picture use the same object's color object by object, because the same object often have the same color. So it makes sense to separate an image into different layers. Each layer contains different objects. And the damaged parts of each layer separately.

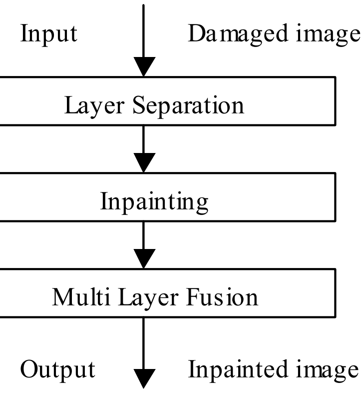


Figure 1. Flowchart of the multilayer inpainting method.

Finally, all inpainted layers are combined the result.The flowchart of the proposed algorithm has been illustrated as Fig. 1. In the next three subsections we discuss these techniques.

A. Layer Separation

In digital inpainting, it is impossible to restore an image to one hundred percents since information is lost. With this in mind, an approximation approach to separate objects into different layers is reasonable for inpainting [2]. This paper proposes a naive layer separation method, which take advantage of SOM’s powerful ability of classification. By the method, pixels of similar colors can be divided into groups, which represent layers.

In this paper, we choose 8bit RGB space as image's color space. So each pixel's color can be denoted by a three dimension uint8 type vector. The network's input is composed by these vectors which represent the colors of useful pixels (i.e. undamaged pixels). And the SOM's task is to divide these vectors into different groups. Because the SOM can automatically classify input vector online, so the only work we need to do here is to decide how many neurons should be used to construct the SOM.

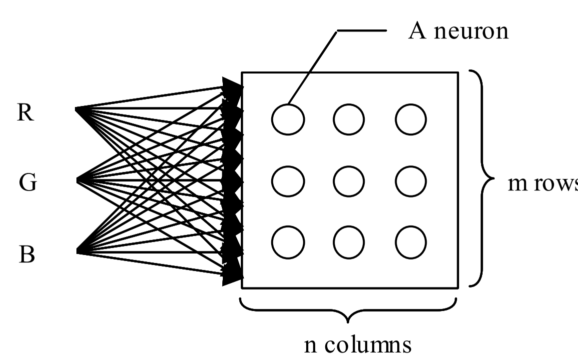
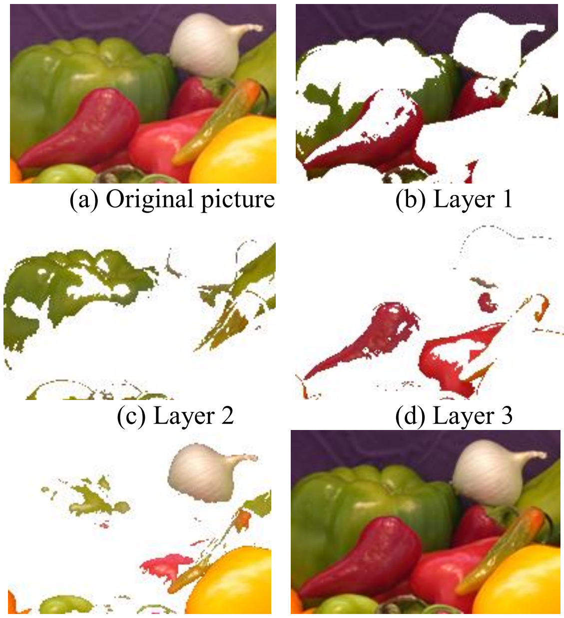


Figure 2. Architecture of the SOM.



(a) Original picture (b) Layer 1

(c) Layer 2 (d) Layer 3

(e) Layer 4 (f) Fusion result

Figure 3. An example of layer separation in 4 layers.

Generally speaking, the more neurons we used, the more layers separated, and the amount of neurons is adjustable. However, when the amount of neurons is as so many as approaching 255, there may be some never inspired neurons. Through experiment we find that, on the one hand, if there are too few separated layers, the final inpainting result will very rough. On the other hand, if there are too many separated layers, not only the damaged pixels may hard to be decided which layers they belong to, and lead to obvious inpainting error, but also taking lots of time for computing. Suppose we construct a SOM having $m \times n$ neurons to separate an image into $m \times n$ different layers. And each neuron has 3 input knobs, for each pixel having three color (Red, Green and Blue) intensity. The architecture of the SOM we used is shown in Fig. 2.

After training the SOM by the input vectors, all the useful pixels can be separate into 9 different groups (layers). A sample of layer separation result is shown in Fig. 3. For the sack of simplicity, we only separate the image into 4 layers.

B. *The Inpainting Algorithm*

In the inpainting approach, the most important thing is to decide the layers to which the damaged pixels belong. We realize that, for a relative large damaged area, the pixels of the area's middle part can not make certain layers for them easily at the beginning of inpainting. Thus, we use an iterative process to inpaint.

We defined the biggest amount of useful neighboring pixels (i.e., UNPs) in each layers of th damaged pixels as $\mu(p_i)$, and the layer in where get the $\mu(p_i)$ as $L(p_i)$. So each damaged pixel have a $\mu(p_i)$ and a $L(p_i)$. In each iteration, the program firstly computes $M(t)$, which equals $\max_i[\mu(p_i)]$, where is the index of the iteration step. And then, each damaged pixel (p_i) whose $\mu(p_i)$ equals $M(t)$ will be restored use the mean color the UNPs in $L(p_i)$. Thus, after each iteration step, the $\mu(p_i)$, $L(p_i)$ and $M(t)$ of the un-restored pixels may be changed.

C. *Multi Layer Fusion*

After all the damaged pixels have been restored, the main task of the inpainting process has been finished. Because each damaged pixel only has been restored in one layer, so if a pixel has a color magnitude in a layer, the position of the pixel in the other layers is blank.

Because we use 8bit RGB space as image's color space in this paper, so the maximum of each color intensity is 255. Therefore the three color (RGB) intensity of blank pixels all are 255. A color image (or layer) which has $m \times n$ pixels can be indicated by a three dimension matrix whose size is $m \times n \times 3$. Thus, the fusion program has three steps. First, the values of the matrixes which represent the layers of an image are subtracted by maximum value, 255. Second, add all these matrixes to a new one. Third, the values of the new matrix are subtracted by maximum value, 255 again. The final result gives a fused image, which is shown in Fig. 3(f).

IV. EXPERIMENTS RESULTS AND ANALYSIS

In this section, we firstly compare the inpainting results of the TV image inpainting scheme [4] and our inpainting method based on an image damaged by disorder lines. And then, we use different amount of neurons to construct different SOM, and compare their inpainting result based on the same damaged image.

Firstly, we compare the results of inpainting between TV inpainting scheme and our inpainting method based on the same 320×256 pixels photo, which is shown in Figure 4(a) as the original image. The photo has been preprocessed. In the process, the color intensity which equal to 255 has been change to 254, so that we can use the 255th color intensity to indicate the damaged pixels. The damaged result of the photo is shown 4(b). The result by TV inpainting scheme is shown in 4(c), and 4(d) are obtained by our inpainting method used a SOM has 3×3 neurons.

We use PSNR (i.e., Peak Singnal to Noise Ratio) value to indicate picture quality of the inpainted image. The PSNR is defined as

$$PSNR = 10 \times \lg\left[\frac{255^2 \bullet Framesize}{\sum_{i=1}^{Framesize}(I_i - P_i)^2}\right] \tag{4}$$

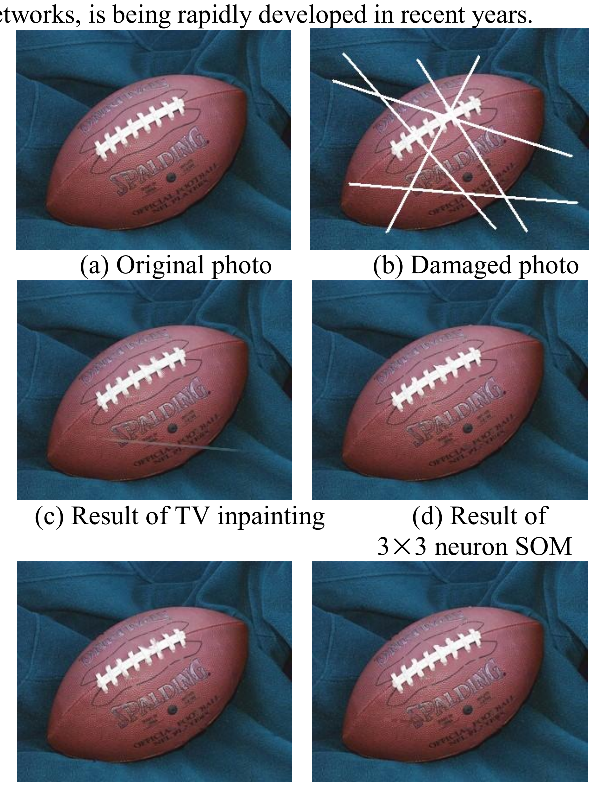
where I_i is i th pixel's original color, and P_i is i th pixel's processed color. The greater PSNR value a processed image has, it is more similar to the original image. Through the calculation we get the PSNR values of Figure 4(b), 4(c) and 4(d), which are 16.8259 dB, 36.5535 dB and 37.9356 dB respectively.

Figure 5(e) and 5(f) show the results of inpainting used 2×2 neuron SOM and 4×4 neuron SOM respectively. Their PSNR values respectively are 37.9087 dB and 37.9006 dB.

V. Conclusions

Automated image inpainting techniques require no particular training or skills from the user to perform complex image restoration. This has an interesting advantage for an ordinary computer user who wants to repair a damaged photo.

A novel approach for image inpainting problem has been proposed in this paper. It is a multilayer inpainting method based on neural networks. Neural networks are composed of simple elements operating in parallel to imitate animals' brain activity. With the rapid development of computer technology, more and more demands have been put to computers. Although the computing speed of computers has been remarkably improved, some easy works for human also can not be complete by computers. So known different from the conventional computing, which is called hard computing, the soft computing, which mainly include fuzzy logic [10], Genetic algorithms [11-12] ,neural networks [13-14], and the combined method of any formers, such as Fuzzy neural networks, is being rapidly developed in recent years.



(a) Original photo (b) Damaged photo

(c) Result of TV inpainting (d) Result of 3×3 neuron SOM

(e) Result of 2×2 neuron SOM (f) Result of 4×4 neuron SOM

Figure 4. Experiment result of inpainting.

The proposed approach takes advantage of SOM's powerful ability of automatically classification to separate an image to several different layers. Thus the approach provides a feasible way to use neural networks in image process.

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