Image Inpainting Using Iterative Methods

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Abstract

Noise interference and data loss are two major problems that affect the processing results of image data transmission and storage. Restoration of the lost information of an image based on the existing information is the essence of inpainting. In this paper a new algorithm based on Sample and Hold interpolation and Iteration is proposed for reconstructing damaged images from existing regions and is compared to some other methods. The experimental results show the superiority of the visual quality and PSNR performance of the proposed method. It is observed that this approach can efficiently fill in the holes with visually plausible information.

1. Introduction

In many applications, we need to reconstruct an image with missing regions from remaining pixels. For example during transmission of images with unreliable channels it may be damaged. The same phenomenon can occur in old paintings and photographs. The aim is to fill-in the lost regions based on the geometric and photometric information such that the human visual system (HVS) is satisfied.

Reconstruction of lost or damaged blocks can be performed in either the spatial (pixel) domain or in the frequency domain. This correspondence proposes a method based on spatial domain information.

There are different algorithms for image inpainting. Generally speaking, these algorithms are categorized in two main categories of image inpainting approaches: Partial Differential Equation (PDE) based approaches [1], [2], [5] and Exemplar based approaches [6]. PDE based approaches try to extend the lines or edges into the inpainting region but they can't restore large areas due to producing blurring effects. These approaches are appropriate for structure images. Exemplar based approaches adopt texture synthesis method to synthesize the pixels in the user specified region. They search all the remaining areas for finding the most similar patch to the target patch. In [7] Criminisi introduced a method which considers the two types of structured and textures images. This method works well especially in the texture target areas but the drawbacks are the introduction of some unwanted objects in the inpainting region and needs much time to fill all the inpainting regions.

This paper is organized as follows: In the next section, the conventional algorithms are reviewed. In section 3, our proposed algorithm is described. Experimental results are discussed in section 4. Finally the conclusion and future work are discussed in section 5.

2. Common Used Algorithms

We first define inpainting problem by giving a damaged image *u* with an unknown region Ω and by trying to find an ideal image *v*.

$$v(x,y) = \begin{cases} \hat{u}(x,y), & if\ (x,y) \in \Omega \\ u(x,y), & otherwise \end{cases} \qquad (1)$$

Thus the goal is to find the best estimation of $\hat{u}$ in the inpainted region Ω. In this section three common inpainting methods are reviewed.

2.1. Exemplar-Based image inpainting

This method combines Texture Synthesis and PDE based approaches to utilize the advantages of both. It means higher filling priority will be given to patches which are located near linear structures; hence these structures are naturally first extended into the gap rather than other patches. With this algorithm, the gap will be filled with non-blur textures, while at the same time preserve and extend the linear structure of the surrounding area.

Considering Fig.1 the steps of this method are described as follows:

1- Define the inpainting region Ω and the patch size. (Fig.1. a)
2- Find all patches located on the border of Ω.
3- Compute patches priority by using the following equation

$$P(p) = C(p).D(p), \qquad (2)$$

where P is a patch, P(p) is the priority term, C(p) is the confidence term and D(p) is the Data term which are described completely in [3]. In this way the most probable patch (ψ_p) is the one that is the continuation of strong edges and surrounded by high-confidence pixels (Fig.1. b).

4- Search in the source region for the most similar patch ($\psi_{q'}$) to the desired patch (ψ_p) (Fig.1. c).

5- Replace the lost information of desired patch (ψ_p) by the data value of $\psi_{q'}$ (Fig.1. d).

6- Do step 2 to 4 until all inpainting regions are filled.
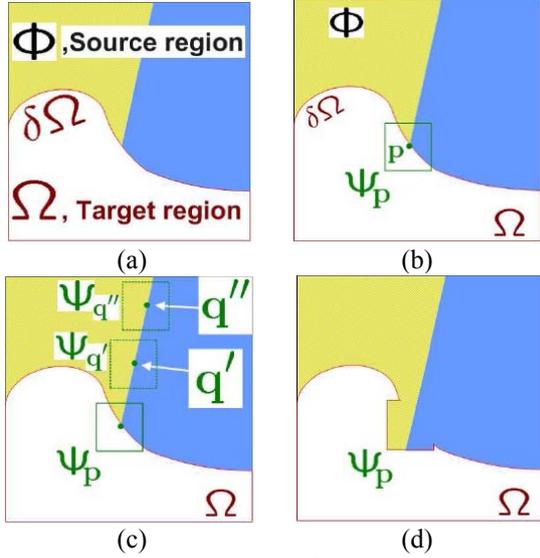

Figure 1. Main steps of Exemplar-Based image inpainting method.

2.2. Total Variation method (TV)

This method is completely described in [1]; briefly we can say that the TV inpainting is modeled by the following mathematical problem

$$\min \int_{\Omega \cup D} |\nabla u| dxdy, s.t. \int_{\Omega} |u - u^0|^2 dxdy = \sigma^2, \quad (3)$$

where u is the given image and u^0 is the initial image, Ω and E, respectively, are the inpainting region and the extended ring of Ω (Fig 5.1 in [1]), and σ is the standard deviation of the white noise. Then the Lagrange form of (3) is:

$$\min \int |\nabla u| dxdy + \frac{\lambda}{2} \int |u - u^{02}| dxdy, \quad (4)$$

where λ refers to the Lagrange multiplier for the constrain on variation.

The steepest descent method can be used for this problem, and the descent is given by

$$\frac{\partial u}{\partial t} = \nabla \cdot \left(\frac{\nabla u}{|\nabla u|_a} \right) + \lambda_e (u^0 - u), \quad (5)$$

where

$$|\nabla u|_a = \sqrt{a^2 + |\nabla u|^2}, \quad (6)$$

The lifting parameter a plays a thresholding role and also improves the condition of TV inpainting model. [1]

2.3. Interpolation using nearest neighbor

Nearest neighbor interpolation method is a spatial domain algorithm, which uses the neighbor's value of the lost pixels. In this paper to achieve better results, interpolation is done in 4 degrees on distorted image and then the average is used. Fig.2 shows the flowchart of this method.

As shown in Fig.2 after doing nearest interpolation, the results are summed and then divided by four; by low pass filtering the resultant image, the result becomes visually better.
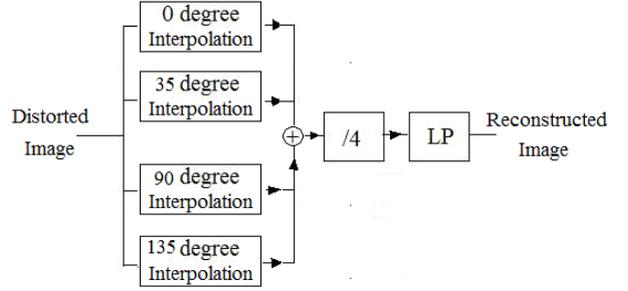

Figure 2. The flowchart of the Interpolation using nearest neighbor method

3. Proposed Method

The proposed method is based on the Sample and Hold (S&H) interpolation and an iterative method. The block diagram of this method is shown in Fig.3. ImD and ImR are, respectively, the distorted and inpainted image.

As shown in this figure, this method includes of 3 blocks: Core, LP and replacement blocks which are described as follows.
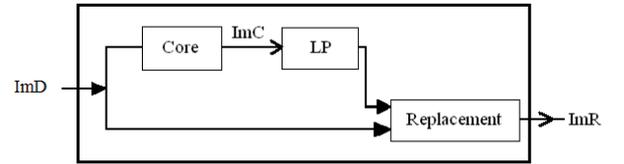

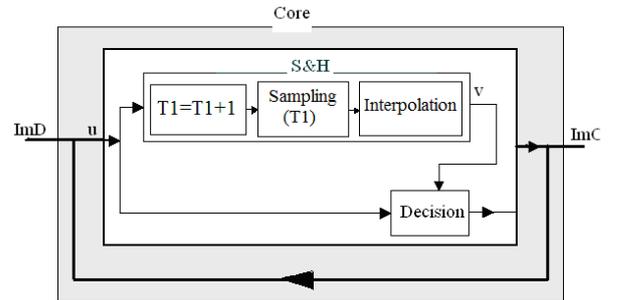**Figure 3.** Block diagram of the proposed method

Figure 4. The Core Block

3.1. The Core block

The Core block is the main part of our algorithm, which contains a loop and two sub blocks: S&H and Decision blocks. Fig.4 shows the diagram of the Core block.

3.1.1. S&H bock

This block contains of a uniform sampling by variant sampling rate of $T1$ which is increased in each iteration and an interpolation which uses the nearest interpolation method. The function of this step is described by (7):

$$X_{SH} = X_{S_{T_1}}(t) * \Pi\left(\frac{t}{T\,1}\right), \qquad (7)$$

X_{ST1} is the sample pixel of image at the sampling time T_1 and $\pi(t/T_1)$ is the Rect function (for more information refer to [4]). The best initial value of $T1$ is 1.

The S&H operation is performed on both rows and columns of current image separately, and then an algorithm defines the best value of these two for each pixel. In this paper, we simply choose the largest value of each pixel between row-interpolated and column-interpolated images for the target image **v**.

3.1.2. The Decision block

The duty of this block is to replace the inpainted region of the input image (**u**) by pixel values of the interpolated image (**v**) which is produced by the S&H block.

3.2. The LP block

In this stage the resultant image of the main block is Low passed for smoothing sharp edges in the inpainted area. The cut off frequency is related to the input image.

3.3. The Replacement block

In the final step, the inpainted region of the previous block is substituted in the original image. In this way we ignore the effect of low-pass filtering on the source region of the original image.

In summaries, first by varying the sampling rate in iterations, we find the closest neighbor of the lost pixels to the furthest one. After that, by filtering the resultant image, we make it more plausible for the human visual system. Finally, by the Replacement block, we make sure that the pixel values in the source region are not changed.

4. Simulations and results

We have simulated all the algorithms in section 2 by using Matlab software. Moreover, the same as all the Inpainting papers, we assume that the mask of the unknown regions is predefined. Since the PSNR values do not perfectly correlate with a perceived visual quality due to the non-linear behavior of the human visual system [8], we judge about the quality of images based on the visual quality; the PSNR of each method is shown in Table. I.

The proposed algorithm has been applied to the standard Lena Image for three different masks and the results of that is compared to the results of three other methods and is shown in Figs.5-7 and compared in Table.I.

In Fig 5, the results of the proposed method and the TV inpainting are very close. Although in this case, the result of the TV method is better visually than our method, the TV method needs 86 iterations to restore the image but the proposed method just needs 12 iterations. The results of the Exemplar-Based and Interpolation methods are not good enough.

As illustrated in Fig.6, the result of the proposed method is obviously better than the other three methods. The result is not only good subjectively, but also it is good in PSNR.

Finally, the efficiency of the proposed method is shown in Fig.7, where three other methods are not acceptable. Although the inpainted image of the Exemplar-Based method is good (Fig.7.d), it consumes about 278 seconds (Table. I). In this case, the proposed method not only could fills the inpainted region in a plausible way for but also it takes only 11 seconds. The results of the TV and interpolation methods are not good because the lost region is made very smooth.

5. Conclusion and Future work

In this paper, an efficient algorithm based on uniform sampling and nearest interpolation method is proposed to fill the missing regions. Experimental results are compared with three common inpainting methods which show that there is a good performance in reconstructing images even when there is a huge lost region. The advantages of this method are that it takes less time than the Exemplar-Based image inpainting method and has more visual efficiency than the TV inpainting technique.

For future work, we would like to improve the decision block of Fig.4.

6. Refrences

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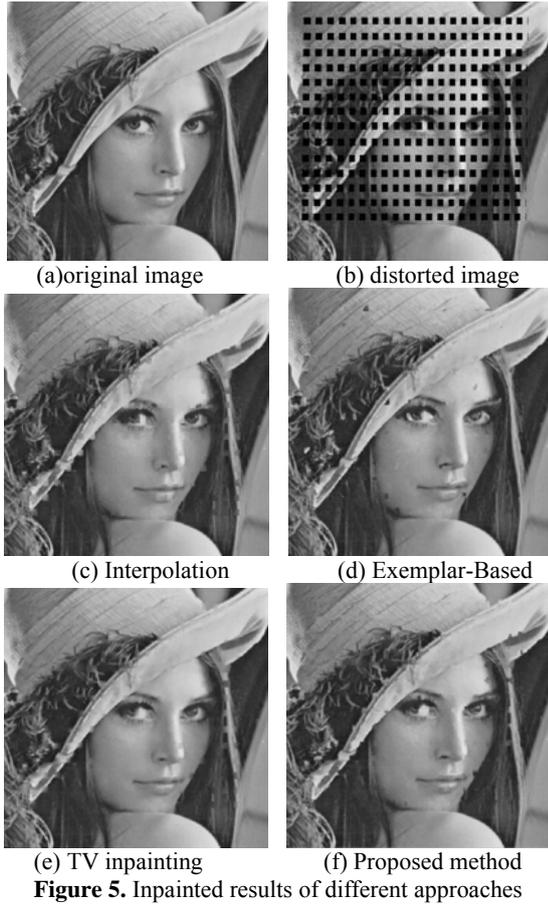
(a)original image   (b) distorted image

(c) Interpolation   (d) Exemplar-Based

(e) TV inpainting   (f) Proposed method

Figure 5. Inpainted results of different approaches

(a)original image   (b) distorted image

(c) Interpolation   (d) Exemplar-Based

(e) TV inpainting   (f) Proposed method

Figure 6. Inpainted results of different approaches

(a)original image   (b) distorted image

(c) Interpolation   (d) Exemplar-Based

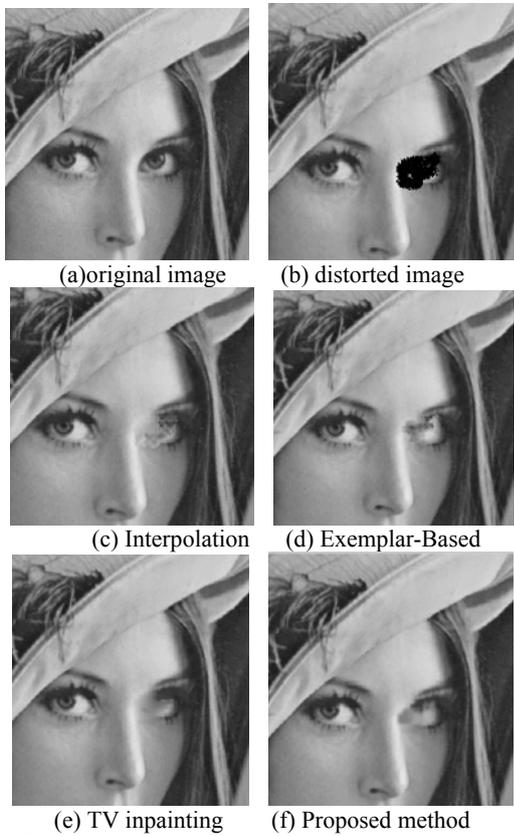(e) TV inpainting   (f) Proposed method

Figure 7. Inpainted results of different approaches

Table I: Comparison between the results of different methods on three different pictures.

Fig 5- PSNR=13.27			
Method	**Proposed Method**	**TV**	**Exemplar-Based**	**Interpolation**
Time	3.18s	3.20s	1968s	400ms
Iteration	12	86	-	-
PSNR	30.02	31.28	29.69	29.27

Fig 6- PSNR=32.78			
Method	**Proposed Method**	**TV**	**Exemplar-Based**	**Interpolation**
Time	2.43s	0.40s	18.27s	400ms
Iteration	8	70	-	-
PSNR	43.65	43.61	40.50	40.84

Fig 7- PSNR=21.97			
Method	**Proposed Method**	**TV**	**Exemplar-Based**	**Interpolation**
Time	11s	4s	278s	400ms
Iteration	42	500	-	-
PSNR	29.94	31.40	30.48	29.86