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A Convolution Based Image Inpainting

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Abstract—**Convolution based image inpainting algorithms are very rapid, however in many cases, they don't provide adequate results in sharp details such as edges. In this paper a novel convolution based image inpainting algorithm is proposed. In the proposed method the mask coefficients are calculated using the gradient of the image to be inpainted. The algorithm is fast, iterative, simple to implement, and provides very adequate results. Experimental results confirm the effectiveness of the proposed algorithm.**

Index Terms—**Image inpainting, Image restoration, image reconstruction, image filtering.**

I. Introduction

Now a day, an important part of scientific and artistic works is stored in form of film and image archive, so image processing becomes a very important task. A new topic in image processing is image inpainting. Image inpainting is filling in damaged or missed regions in an image in an undetectable form. It has several applications such as image reconstructing, video restoration, special effects and so on.

In general there are three groups of image inpainting algorithms. First group reconstructs an image by solving a proper Partial Differential Equation (PDE), the second group uses texture synthesis to inpaint missed regions of image, and finally, third group includes convolution-filter based algorithms.

A. PDE Algorithms:

In such a method, a PDE is designed to connect edges or isophotes (line of equal gray values). In [1] Bertalmio et al. proposed an image inpainting algorithm based on PDE. Its algorithm will have good results if missed regions are small, but in large damaged regions it will take so long time and wont have good results. In [4] Bertalmio et al. use similarities between image processing and fluid dynamic topics, and he proposed an image inpainting algorithm using the Navier-Stokes equation. Chan et al. [5-7] present several inpainting algorithms such as total variation (TV), curvature driven diffusion (CDD), and Euler's elastica. In [5] authors try to minimize the TV-norm of reconstructed image in order to restore damaged pixels. Chan and Shen [6] use energy functional involving the curvature of the level curves and tries to connect level curves in a smoothing fashion. Masnou and Morel in [20] present a new model for image inpainting. They propose a simple but effective algorithm to connect level lines. Some works relate phase transition in supper conductors to image inpainting [16,17]. Authors in [22] propose an algorithm that propagates tangential and normal vectors into missed regions then it reconstructs damaged image by fitting it to these vectors. Telea [8] propose a fast marching method that can be considered as a PDE method which is faster and simpler to implement than other PDE based algorithms. All of above mentioned algorithms are very time consuming and have some problems with the damaged regions with a large size.

B. Texture Synthesis Algorithms:

Texture based algorithms fill in damaged or missed regions using similar neighborhoods in an image, i. e. they try to match statistics of damaged regions to statistics of known regions in the neighborhood of a damaged pixels. In [12] Efros et al. proposed a nonparametric texture synthesis model based on Markov random field to inpaint textural images. In his method first a neighborhood around a damaged pixel is selected. Then all of known regions of the image are searched to find the most similar region to the selected neighborhood. Finally, the central pixel in found neighborhood is copied to damaged pixel. This model is really time consuming and it doesn't have good result in structure regions. Criminisi et al. [27] modified model in [12] by three changes:

- The whole neighborhood is copied instead of the central pixel.
- He introduced a priority for the pixels, i. e. pixels near an edge or known pixel have higher priority, and inpiant pixels with higher priority before low priority pixels.
- He limited the search space.

This algorithm achieves better results in both speed and visual quality than presented algorithm in [12]. Chang et al. [21] showed that the priority function adopted in [27] is not a well-defined function and may become unreliable after a number of iterations. Therefore they proposed a new function to assign priority to pixels providing a robust exemplar based algorithm.

Some approaches combine both above groups (PDE and texture synthesis) to restore damaged pixels. Bertalmio et al. [13] propose decomposing image in to two sub-images

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(structural and textural sub-images), and then inpainting each sub-image with a related model. In [11], authors propose a very similar algorithm in which, instead of decomposing the damaged image in to two sub-images, it is segmented into two kinds of sub-regions.

C. Convolution-Filter Based Algorithms:

A convolution-filter based algorithm inpaint an image by convolving the neighborhood of the damaged pixels with a proper kernel. Oliveira et al. [3] presents a fast image inpainting algorithm which uses convolution operation. In their algorithm, the regions to be inpainted are convolved with a predefined diffusion mask repeatedly. This model is very similar to isotropic diffusion. In this method, the central weight of the diffusion mask is considered zero, because its related pixel in the original image is unknown. In [2] Hadhoud et al. present a modification of Oliveira algorithm permitting an implementation time reduction. Both above convolution based algorithms are very quick but they don't have very good results in high contrast damaged edges.

Recently several algorithms are proposed that use non local information to estimate pixels in missed regions. Wong and Orchard [25] propose a new approach that uses exemplar based algorithm to inpaint damaged regions. In this approach, algorithm searches similar neighborhoods in all regions of image instead of limited region. Li et al. [26] present a non local curvature driven diffusion model for image restoration. In this method, first algorithm finds similar regions in original image then it utilizes a CDD algorithm to reconstruct damaged regions from found neighborhood.

Expecting convolution-filter based algorithms, other methods are very time consuming however providing acceptable results in structural or textural regions. While convolution-filter based algorithms result in blurring in such regions.

To overcome this drawback, in this paper a new convolution based algorithm is presented. In the proposed method, the kernel weights are considered as a predefined function of the image gradient value in the neighborhood of a missed pixel. The proposed approach is fast, iterative, simple to implement and provides as well results as structure algorithms in structure regions.

The organization of the paper is as follows. The proposed method is presented in section 2. Experimental results are presented in section 3 where a comparative study is done. Finally a conclusion is given in section 5.

II. Proposed Convolution Based Image Inpainting

The main idea of the proposed convolution based inpainting algorithm, is to use an adaptive kernel permitting a better processing edge regions. To do this, we use the gradient of known pixels in the neighborhood of a missed pixel to compute weights in convolving mask. Since gradient values in edge regions are large, and contribution of pixels in adjacent of edges should be less than contribution of pixels in smooth regions, we propose that weights be computed by a predefined function of the image gradient. By according zero or small weights to missed pixels' neighbors with large local gradients, edges will be preserved better (i.e. weights of convolution mask changes adaptively with gradient of pixels in a neighborhood). Thus, the algorithm can estimate missed pixels while preserve sharp edges in image. The problem is to design a function that is reciprocal to the gradients for smooth estimating and edge maintaining. We propose a function F(x) as follows to compute weights from the image gradient.

$$F(x)=\begin{cases}1-(\frac{x}{\alpha})^2 & \text{if } |x|\le\frac{\alpha}{2}\\ (\frac{x}{\alpha}-1)^2 & \text{if } \frac{\alpha}{2}\le|x|\le\alpha\\ 0 & \text{if } |x|\ge\alpha\end{cases}\qquad(1)$$

Where x is gradient value of the current pixel in the image, α is a parameter giving an estimation of the missed pixel gradient and it control the softness of propagation. We opt for this function because it matches well our purpose, and it is simple and fast to compute.

The algorithm is as follows. First a missed pixel on boundary of the damaged region is chosen; next a neighborhood around it is considered and central gradients for each known pixel in the mask, is calculated, finally, the weights are computed as following:

$$w(k)=\tfrac{1}{n}F(x_k)\qquad(2)$$

Where k presents the pixel position and w is the kernel weight at k, and n is the number of known pixel in the current neighborhood. Finally a value for a damaged pixel is calculated as follow:

$$f'(p)=(1-\sum_{k=1}^{n}w(k))f(p)+\sum_{k=1}^{n}w(k)f(k)\qquad(3)$$

In that *f'(p)* is estimated value, *f(k)* is value of a known pixel in the current neighborhood, *n* is the number of known pixel in the current neighborhood.

Let a neighborhood around a missed pixel, P, be as in fig. 1:

P_1	P_2	P_3
P_4	P	P_5
P_6	P_7	P_8

Fig. 1. A neighborhood around a missed pixel P.

Central gradient for a pixel is defined as deference between value of the pixel and value of central pixel, i. e. the central gradient of Pk is defined by:

$$x_k = f(P_k) - f(P) \tag{4}$$

The pseudo-code of the algorithm is represented in fig. 2.

```
For iteration 1 to m
{
Choose a neighborhood
Compute central gradient of known pixels using 4
Calculate weights using function in relation 1 & 2
Estimate damaged pixels using 3
If difference between two last obtained images is less than a user defined number, break
}
End
```

Fig. 2. Pseudo-code of presented algorithm.

III. Experimental Results

To evaluate the performance of the proposed algorithm in this section several comparative experiments are performed. We applied the proposed algorithm as well as a PDE based, Oliveira algorithm and Hadhoud algorithm to several damaged images of different contains. The experiments are performed on a 2.93 GHz PC. The qualitative results are shown by Figs. 3 to 5 and α is considered 1(or 255) in the first iteration since if it is not, it might a black region missed and its color change to white so value of gradient is equal to 1(or 255) therefore all weights become zero and no value will be assigned to damaged pixels, in the other iterations it is set to 0.1 (or 20). In fig. 3, the image contains a large missed region, as this figure suggests all Bertslmio, Oliveira and Hadhoud algorithms lead to blurring and can not preserve edge adequately, but the proposed algorithm achieve a very adequate result. In fig. 4, an image with several damaged region is illustrated. Here, the proposed algorithm provides the best result among all presented algorithm too. In Fig. 5, a damaged color image, corrupted by thin texts is considered. The algorithms are applied to each color components of the image separately. As this figure suggests both Oliveira algorithm and proposed algorithm, provide adequate results. Therefore we can conclude that for a large damaged region, the proposed algorithm provides better results than others (even than a structure algorithm), Oliveira give as well results as our algorithm only for small missed regions, and Hadhoud algorithm give good results only in smooth regions. Table I shows the run time of these algorithms. According to this Table, the Hadhoud algorithm is the fastest, but its qualitative results are not adequate. The proposed algorithm is faster than rests.

TABLE I
TIME OF IMPLEMENTATION

algorithm	Figure 3	Figure 4	Figure 5
Bertalmio	388.16	1487.41	3013.44
Oliveira	15.6	8.51	10.72
Hadhoud	0.002	0.002	0.013
Proposed	13.61	25.17	19.99

IV. Conclusion

In this paper a new convolution based algorithm is proposed. The proposed algorithm is adaptive and uses gradient to calculate weights of convolving mask at each position. To assign low weights to pixel near an edge a predefined function permitting better preserving the edges is introduced. The algorithm is fast, iterative, simple to implement and provides as well results as structure algorithms. The experimental results confirmed the effectiveness of the algorithm.

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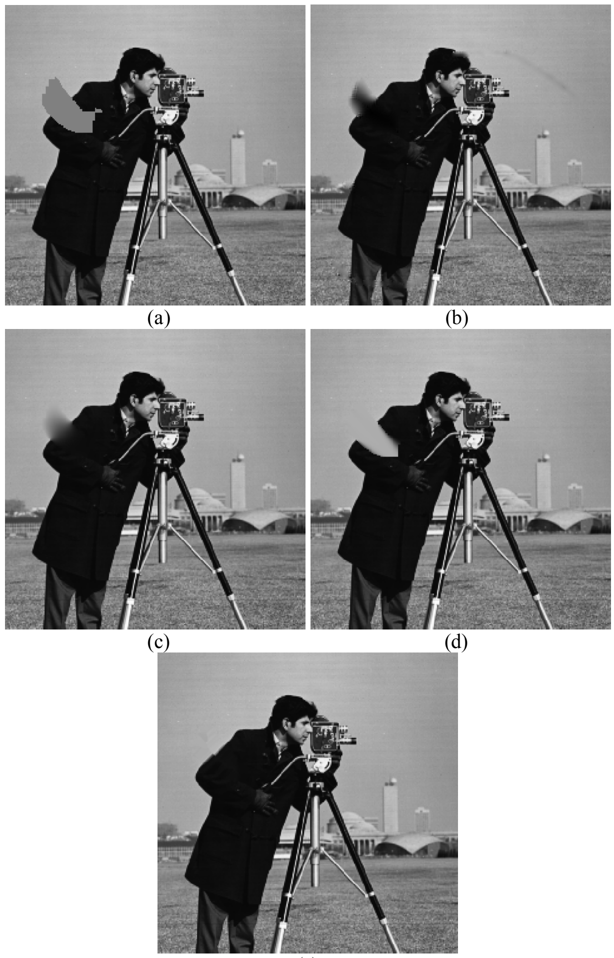

Fig. 3. a) damaged image b) inpainted with Bertalmio algorithm [1] c) restored by Oliveira algorithm [3] d) reconstructed with Hadhoud algorithm [2] e) inpainted with proposed algorithm.

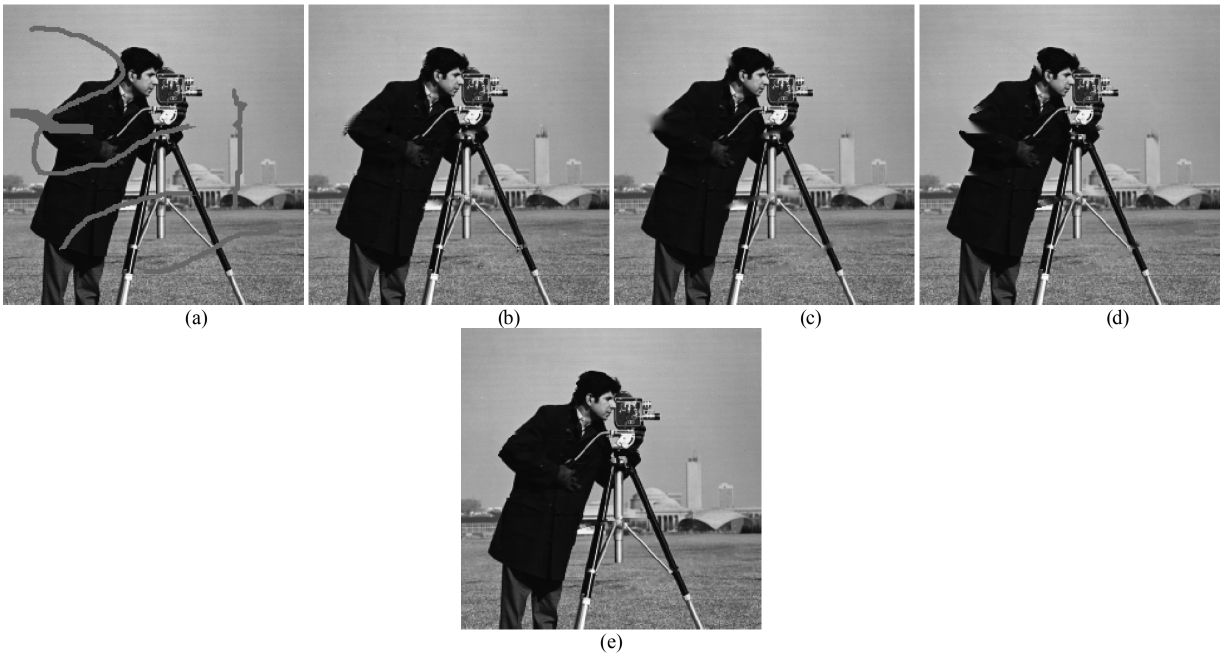

Fig. 4. a) damaged image b) inpainted with Bertalmio algorithm [1] c) restored by Oliveira algorithm [3] d) reconstructed with Hadhoud algorithm [2] e) inpainted with proposed algorithm.

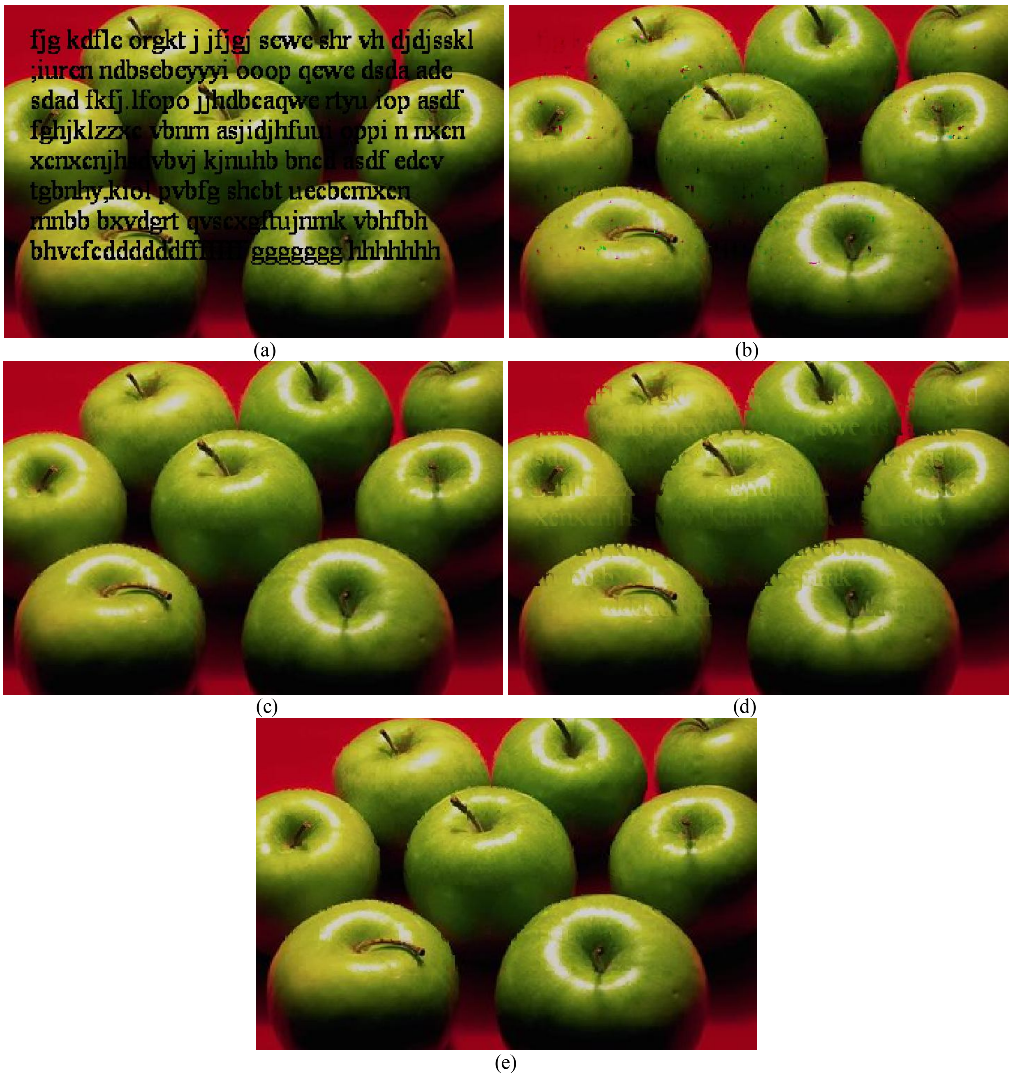

Fig. 5. a) damaged image b) inpainted with Bertalmio algorithm [1] c) restored by Oliveira algorithm [3] d) reconstructed with Hadhoud algorithm [2] e) inpainted with proposed algorithm.