A new vector method for color image inpainting

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Abstract: Among numerous inpainting methods that have been proposed, convolutional based methods are rapid and simple with respect to others. However, the major flaw of these methods is that sharp edges are not inpainted properly, and usually smoothed. In this paper, a new fast convolutional inpainting method is proposed for color images that is edge-preserving and could estimate the missing parts of an image effectively. In the proposed algorithm, the convolutional mask coefficients are calculated according to the gradient information at each pixel in three layers of color image. Experimental results confirm the simplicity and effectiveness of our method with respect to some other recent methods.

Key words: image inpainting, convolutional mask, directional gradients.

1. Introduction

Image inpainting is the process of filling damaged or missing regions in an image using information from surrounding areas. Typical application of inpainting includes restoration of old images and removing scratches from photographs [1]. The first digital inpainting work was introduced by Bertalmio and Sapiro in 1999 [1]. This model is based on the nonlinear partial differential equations (PDE), and imitates the techniques of artists who restore damaged parts in images. In fact, in this algorithm, gray level information from surrounding areas is propagated into the damaged part. Subsequently, Bertozzi depicted that there exist a connection between Bertalmio’s work and the 2-D fluid dynamics through the Navier-Stokes equation, and proposed an inpainting method based on this equation [2]. Chan & Shen propose a different approach to tackle image inpainting problem [3]. Their algorithm was based on the total variation denoising approach presented in [4] and could propagate sharp edges into the inpainting zone properly. However, because of the regularization term, their model imposed a penalty on the length of edges, and thus the inpainting model couldn’t connect contours across very large distances.

In the recent years, some new inpainting methods have been proposed by researchers [5-11]. In [5] an inpainting method based on illumination variation and structure consistency is proposed. This method uses confidence and illumination variation factors to determine the priority of the filling order of target (damaged) regions. In fact, by using these two factors it proposes a dynamic rule to pick the best target region, and the suitable patch size in each filling step. Yang proposes an image inpainting algorithm using complex 2-D dual tree wavelet transform [6]. In [7] an improved method for color image inpainting is proposed. In this approach, a guided vector field is created by employing source and target image within a selected region using Poisson’s equation at first. Then, the guided vector is used in generating the result image. In [8] an inpainting method using geometrical grouplets is proposed. The grouplets are used to represent the complex geometry of the image to be inpainted. In the proposed method, after representing the image geometry by grouplets, missing data are synthesized by propagating the geometrical information from outside to the inside of inpainting zone. Barcelos et al. proposes a new inpainting method based on geodesic paths in the image [9]. The geodesic method produces good inpainting results, especially when the inpainting domain is little. The main drawback of the mentioned method is that these methods are time-consuming, and recovering lost parts of an image takes a lot of time. A group of image inpainting methods that is fast and effective is convolutional methods [10-11]. In these methods, a mask kernel is convoliled with windows in image to produce missed pixels. A drawback of these methods is that the sharp edges are not inpainted properly.
In this paper, a new convolutional image inpainting is proposed for color images. The method uses directional gradients in three layers of color image (R, G, B) in a vector fashion, and effectively inpaints missing parts of the image.

Structure of this paper in the following is as follows. In Section 2, Fast inpainting method is demonstrated. Section 3 includes our proposed algorithm for color image inpainting. In Section 4, our implementation results are shown, and finally in Section 5 the paper will be concluded.

2. Fast Oliveira’s inpainting method

In the Oliveira’s inpainting method [10] it is assumed that \( \Omega \) is a small area to be inpainted and \( \partial \Omega \) is its boundary. Since \( \Omega \) is small, the inpainting procedure can be approximated by an isotropic diffusion process that propagates information from \( \partial \Omega \) into \( \Omega \). The fast method consists of initializing \( \partial \Omega \) by clearing its color information and repeatedly convolving the region to be inpainted with a diffusion kernel. \( \Omega \) is a one-pixel thick boundary and the number of iterations is independently controlled for each inpainting domain by checking if none of the pixels belonging to the domain had their values changed by more than a certain threshold during the previous iteration. Alternatively, the user can specify the number of iterations. As the diffusion process is iterated, the inpainting progresses from \( \partial \Omega \) into \( \Omega \). Convolving an image with a Gaussian kernel (i.e., computing weighted averages of pixels’ neighborhoods) is equivalent to isotropic diffusion (linear heat equation). Ordinarily, the fast method uses a weighted average kernel that only considers contributions from the neighbor pixels (i.e., it has a zero weight at the center of the kernel). Fig. 1 shows two masks that are used for convolution action in Fast method. It should be mentioned that in the Fast method, for color image inpainting, convolution action is done for each color component (R, G, B) independently.

![Convolution masks](image)

3. Proposed method

The Fast inpainting method that demonstrated in Section 2 has some deficiencies. Firstly, it is suitable for inpainting of small missing or damaged regions in images. Secondly, as the coefficients in the convolution mask have a uniform distribution in all directions. Therefore, the sharp edges are smoothed. So, in this paper in order to construct sharp edges properly, we propose the coefficients in the mask calculated adaptively by using the information of edges.

Our algorithm for color images inpainting is as follow.

1- For each pixel in the damaged area in each color layer (R, G, B) eight directional gradients are calculated. Supposing that \( u(i, j) \) is the target pixel to be inpainted, eight gradients for first color layer (R=Red) are calculated using equations (1)-(8). Fig. 2 shows eight selected directions for calculating gradients.

![Selected directions](image)

\[
\begin{align*}
G_{1_r} &= u_r(i, j) - u_r(i - 1, j - 1) \\
G_{2_r} &= u_r(i, j) - u_r(i, j - 1) \\
G_{3_r} &= u_r(i, j) - u_r(i + 1, j - 1) \\
G_{4_r} &= u_r(i, j) - u_r(i + 1, j) \\
G_{5_r} &= u_r(i, j) - u_r(i + 1, j + 1) \\
G_{6_r} &= u_r(i, j) - u_r(i, j + 1) \\
G_{7_r} &= u_r(i, j) - u_r(i - 1, j + 1) \\
G_{8_r} &= u_r(i, j) - u_r(i - 1, j)
\end{align*}
\]

Similarly, gradients for two other color layers (G, B) are calculated.

2- After calculating directional gradients in step1, for each direction around target pixel, a gradient vector is obtained that has three components as follow.

\[
G_i = (G_{ir}, G_{ig}, G_{ib}) \quad , i = 1, 2, 3, ..., 8
\]
3- For each direction, magnitude of the gradient vector is calculated using equation (10).

\[
|G_i| = \sqrt{G_{ir}^2 + G_{ig}^2 + G_{ib}^2}, \quad i = 1, 2, 3, ..., 8
\]  

(10)

4- For calculating coefficients in the convolution mask, we use a reciprocal function (F) that acts similar to Gaussian function. Our proposed function is as follow.

\[
F(G_i) = \begin{cases} 
\text{sinc}(|G_i|) & \text{if } 0 < |G_i| < 0.5a \\
\text{abs}\text{sinc}(|G_i|) & \text{if } 0.5a < |G_i| < a \\
0 & \text{otherwise}
\end{cases}
\]  

(11)

In which ‘a’ is a parameter that controls the softness of propagation and is optimized for each image separately by trial and error in order to achieve best quality for result image.

It can be derived from (11), for each direction only one value is calculated. Then, the mask for convolution is calculated using (F) as Fig. 3.

\[
\begin{array}{ccc}
F(G_1) & F(G_8) & F(G_4) \\
F(G_2) & 0 & F(G_5) \\
F(G_3) & F(G_4) & F(G_5)
\end{array}
\]

Fig.3. Convolution mask in our proposed method

Then, for each pixel in the target area, a 3x3 mask is chosen around it. Afterwards, it is convolved repeatedly with the convolution mask calculated above. Some advantages of our method are that:

1- Sharp edges are not smoothed because coefficients of the convolution mask are chosen adaptively with the gradient information.

2- A uniform mask is used for convolution in all color components. This means that by using magnitude of gradient vector and calculating the corresponding coefficient in the mask, only one mask is achieved that is proper for all three layers (R, G, B).

4. Simulation Results

The proposed method is applied on a different set of color images including ‘Apples’, ‘Lena’, ‘underwater’. Parameter ‘a’ is selected optimally in the range [10, 20] so that the result image achieves the best quality. For comparison, Fast Oliveira’s method is selected as a convolutional method [10] with two different masks, and geodesic method [9] is selected as a recent effective inpainting method. The results of inpainting ‘Lena’, ‘Apples’ and ‘underwater’ images with different missing parts are shown in Fig. 4, 5 and 6 respectively.

The inpainted results show that our method is much more efficient for inpainting of large damaged regions in comparison to other three methods. In addition, it can be seen that in the proposed method, sharp edges are inpainted properly and are not smoothed.

5- Conclusion

Image inpainting is one of the interesting research topics in the image processing field. In this paper, a new fast image inpainting is proposed based on convolutional masks. The proposed method exploits directional gradients, and can restore sharp missing edges effectively. The simulation results confirm the efficiency of the proposed method in comparison to some recent image inpainting methods.

References

Fig. 4. Comparison of different methods in image inpainting. a) Original "Lena" image. b) Image with large scratch areas. c) Oliviera’s Fast method [10] using mask b (processing time=32.85 s) d) Oliviera’s Fast method [10] using mask a (processing time=32.9 s) e) Geodesic method [9] (processing time=18.7 s). f) Proposed method (processing time=125.1 s)
Fig. 5. Comparison of different methods in image inpainting. a) Original ‘Apple’ image  b) Image with large text c) Oliviera’s Fast method [10] using mask b (processing time=28.7 s). d) Oliviera’s Fast method [10] using mask a (processing time=28.6 s). e) geodesic method [9] (processing time=582.24 s). f) Proposed method (processing time=74.7 s).
Fig. 6. Comparison of different methods in image inpainting. a) Original ‘Underwater’ image. b) Image with missed parts. c) Oliviera’s Fast method [10] using mask b (processing time=34.4). d) Oliviera’s Fast method [10] using mask a (processing time=35.24s). e) geodesic method [9] (processing time=85.7s). f) Proposed method (processing time=140.24s).