EXEMPLAR BASED IMAGE INPAINTING WITH IMPROVED PRIORITY FUNCTION

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Abstract: Digital image inpainting is a technique used for filling in the disappeared or spoiled regions of an image using information from the surrounding area. Image inpainting provides a means to restore damaged region of an image, such that the image looks complete and natural after the inpainting process. Exemplar-based algorithms are a popular technique for image inpainting, in which two important parts: deciding the filling-in order and selecting good exemplars. Criminisi’s approach is to search suitable patches from source regions to fill in the missing parts, but face a problem that: unsuitable selection of exemplars. To improve the problem, we introduce a self-governing approach through investigating the process of patches propagation. Defining a new separated priority function to propagate geometry and then synthesize image textures, aiming to well recover image geometry and textures. Compared to other approach, the improved priority definition can recover image geometry and textures well.

Keywords: Exemplar based Approach, Improved Priority Function, Inpainting, Priority computation.

INTRODUCTION

In the present scenario, image inpainting techniques are very popular in the field of image processing and computer graphics which refers to restoring or preserving the distorted or missing regions of the image. The operator is to recognize the omitted or spoiled areas quantitatively, since these areas cannot be simply categorized. These identified regions are called inpainting area or target regions and the unspoiled parts, whose evidence are used to repair the target region, are called source regions. The main objective of inpainting is to “guess” the lost information according to surrounding image information. All methods are guided by the postulation that pixels in the known and unknown parts of the image share the same numerical properties or geometrical structures. This postulation converts into different local or global priors, with the objective of having an inpainted image as physically believable and as visually attractive as possible. Applications of this technique include the restoration of old photographs and damaged film; removal of superimposed text like dates, subtitles, or publicity; and the removal of entire objects from the image and to give special effects.

A large amount of research is going on for developing the new and better inpainting algorithms. The first type of the image inpainting algorithms is the “Diffusion-based
Inpainting”. Bertalmio et al. [1] proposed the PDE-based method for inpainting. Inspired by the concept of manual inpainting, this method tries to translate the rules into a mathematical and algorithmic language which are used in manual inpainting. Inspired by the work of [1], Chan and Shen [2, 3] proposed two image-inpainting algorithms viz. the Total Variational (TV) inpainting model [2] and Curvature-Driven Diffusion (CDD) model [3]. The TV inpainting model uses a Euler-Lagrange equation to inpaint the region. This model was designed for only small regions’ inpainting and it removes the noise but fails into connecting the broken edges. The CDD model is the extension of the TV algorithm which also takes into consideration the geometric information of the isophotes and allows the inpainting to proceed over larger areas as well. CDD has ability to connect some broken edges, but the resulting image contains the blurriness.

The methods discussed above only recover the structural part of the image and produces the blurriness. It suffers from the problem of texture restoration. So, for texture restoration, several researchers used the texture synthesis method [4] which is the second type of the inpainting algorithms. The texture synthesis method is slightly different from image inpainting. The goal of texture synthesis approach is to create a texture from a given sample in such a way that the created texture is larger than the source sample with a similar visual appearance. Texture synthesis methods directly apply to the inpainting problem where the source part or known part of the image can be seen as the input texture sample from which the missing pixels can be learned and the new image with a large area than the source sample is generated. There are two types of texture synthesis methods viz. pixel based and patch based. Patch based methods take less time than the pixel based methods. But this method only recovers the textural part of the image. The simultaneous structure and texture inpainting is given in [5]. In this, the image is decomposed into two parts, one containing the structure and other containing texture. Then these images are inpainted individually and then combined to get the output image. But this approach is not appropriate for thick damaged regions and repairing large region, because it produces blurring artifacts, as the PDE-based approach is used to construct the structural component. This drawback is fulfilled by the Exemplar-based inpainting method [6], which is the third and the main category of the image inpainting algorithms. This type of image inpainting algorithms has proved to be very successful. Basically, exemplar-based approach comprises two fundamental steps: In the first step, the priority assignment is done and the second step comprises the selection of the best matching patch. In the priority assignment, the priority term is computed, which contains confidence term and data term. The confidence term is used for the textural information and the data term is used for the structural information. The confidence term used in [6] approaches to very small values quickly as the process of filling proceeds. So, the computed priority becomes almost indistinguishable. So, in this paper, define new Improved Priority function in exemplar based inpainting. the improved priority definition can recover image geometry and textures well. The inpainting based on new IP function efficiently improves the PSNR and SSIM values than criminisi method.
The paper is organized as follows. The proposed method is described in Section II. The performances of the method are discussed in Section III. Finally, Section VI concludes the paper.

PROPOSED WORK

A. Basics of Exemplar-based technique

The exemplar-based technique was first proposed by Criminisi et al. [6]. In this technique, the source region or the known region is given by (Φ) and the damaged or the unknown region is given by (Ω). First of all, the region which is to be inpainted is marked with a uniform color whether it is the damaged region or the object which is to be removed. The exemplar-based inpainting works in an iterative manner. First of all, the boundary of the unknown region is detected. After that, for all the pixels on the boundary, the priority is computed by using the confidence term and the data term. The confidence term C(p) and the data term D(p) are computed by (1) and (2) as,

\[ C(p) = \frac{\sum_{q \in \partial \Omega} C(q)}{|\psi_p|} \]  
\[ D(p) = \frac{\|\nabla n_p\|}{\alpha} \]  

Here, \(\psi_p\) is a patch with center pixel \(p\); \(I\) is entire image and \(\Omega\) is target region. \(C(q)\) represents the confidence value for pixel \(q\) which belongs to a patch centered at pixel \(p\) which is already known. \(|\psi_p|\) is an area of patch, \(n_p\) is vector normal to structure at pixel \(p\) and \(\alpha\) is normalization factor. Priorities are calculated by multiplying the confidence term and data term as given in (3).

\[ P(p) = C(p)D(p) \]  

Once priorities are found, the patch having maximum priority, say \(\psi_{\hat{p}}\) is selected. For that selected patch, the most similar patch is searched from source region \((I-\Omega)\) using Sum of Squared Distance (SSD). Best patch \(\psi_q\) is found using (4) as given below. \(d(\psi_\alpha, \psi_\beta)\) is the distance between two generic patches and is defined as SSD of already filled pixels in two patches. Information from the best-match-patch is now copied to the highest priority patch. This method helps preserving structure as well as texture information.

\[ \psi_q = \arg\min_{\psi_q \in \Omega} d(\psi_\hat{p}, \psi_q) \]  

In all of this process, the main important terms are confidence term and data term. In both of these terms, the data terms preserved the linear structures. It depends on the isophotes that defines the minimal change of the intensity.

B. Exemplar-based approach with Improved Priority Function

An image is generally consisted of geometry and textures. For Criminisi’s method, it tends to propagate the geometry and textures into the target region simultaneously, since the priority definition of Criminisi’s method is determined by two terms, one is the confidence term that encourages textures propagating, and the other is the data term that prefers to propagate geometry. Although the way to propagate geometry and textures simultaneously obtains excellent results, it sometimes appears significant miscopies or makes image geometry being destroyed.
To design a separated priority definition that is determined by the data term first and then by the confidence term. The new improved priority can propagate image geometry into the target region first, then synthesize textures. The new definition is given as follows,

\[ P(p) = \begin{cases} D(p) & \text{some iteration} \\ C(p) & \text{after data terms} \end{cases} \]

Criminisi's method [6] gets excellent results for image inpainting, but this approach has to encounter a drawback that it needs expensive computation. Because Criminisi's method has to search the most similar patch by Eq. (4) within the whole source image \( \Phi \). In this work, utilize a simple patch-in-patch approach to reduce the expensive computation. This approach selects the most similar patch within a bigger patch \( \psi_p' \) but the whole source image \( \Phi \). Just need to change Eq. (4) slightly to get the new exemplar selection method that is used to measure the similarity between two patches,

\[ \psi_q = \arg \min_{\psi_q} d(\psi_p, \psi_q) \]

where \( d(\psi_p, \psi_q) \) is defined as the sum of squared differences (SSD) of the already filled pixels between the two patches \( \psi_p, \psi_q \) and \( \psi_p' \) is the bigger patch with same center \( p \) with \( \psi_p' \).

This strategy can prevent image geometry from being destroyed effectively, and reconstruct image textures well. In addition, this improved priority definition also works well for the case of curved or cross-shaped structures. The improved priority function method showed better visual results than criminise’s exemplar-based method for the case of curved or cross-shaped structures. In particular, this method performed not so well for the case of that geometry changed direction strongly, e.g., the corner of triangle.

**EXPERIMENT RESULTS AND COMPARISON**

The algorithms were simulated on 2.20 GHz Intel(R) Core(TM) i5 with 8.00 GB RAM running under 64-bit Windows 10 Home operating system. The software used for simulation was MATLAB R2009b.

Simulation results for object removal using Criminisi [6] and exemplar based approach with IP function are compared. As shown in Figure 1, we can visually see that exemplar based inpainting with Improved Priority function gives better results compare with Criminisi algorithm. IP function method recovers the image well when giving a larger target region, while Criminisi’s method leaves significant miscopies. It demonstrates that IP function method is more robust to varying and large target regions than Criminisi’s method.

![Figure 1: Inpainting of fengche0 image by criminisi method and IP function](image-url)
The same procedure is followed into figure2, figure3 and figure4, in which comparison between criminici method and IP function method shown. From the results, we can see that IP function approach gives better visual results. IP function method performs better, because it protects the image geometry well. Criminisi’s method however slightly copies wrong patches from the source region (see the close-ups).

Table 1 shows the comparison of different PSNR values (represents a measure of the peak signal to noise ratio) using different methods and the comparison of SSIM values (represents the structural similarity) using different methods.
Table 1: Comparison of PSNR and SSIM

<table>
<thead>
<tr>
<th>Original Image</th>
<th>Fill image</th>
<th>Resolutions</th>
<th>PSNR Inpainted</th>
<th>SSIM Inpainted</th>
<th>PSNR Inpainted with IP</th>
<th>SSIM Inpainted with IP</th>
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</thead>
<tbody>
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<td>bungee0.png</td>
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<td>39.08116</td>
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<td>48.89143</td>
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CONCLUSION

- Exemplar based image inpainting used combine structure and texture synethesis approaches. So it’s give effective results of smooth images with medium or big holes, but for highly texture images produce some errors.
- In this paper, presented a new separated priority definition for exemplar-based image inpainting. The Improved priority function method could handle inpainting problems with large target regions.
- Exemplar based approach with improved priority function showed better visual results than compared to exemplar-based method by criminisi for the case of curved or cross-shaped structures. But IP function method performed not so well for the case of that geometry changed direction strongly.

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