A Comparative Analysis of Exemplar Based Image Inpainting Algorithms

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Abstract

Image inpainting refers to the task of filling in the missing or damaged regions of an image in an undetectable manner. Many researchers have proposed a large variety of exemplar based image inpainting algorithms to restore the structure and texture of damaged images. However, no recent study has been undertaken for a comparative evaluation of these algorithms. In this paper, we are comparing various exemplar based image inpainting algorithms which do not have diffusion related blur in the result image. The analyzed algorithms are Antonio Criminisi et al’s Region filling algorithm, Jiying Wu et al’s Hybrid algorithm and Zhaolin Lu et al’s Image completion algorithm. Both theoretical analysis and experiments have made to analyze the results of these exemplar based image inpainting algorithms on the basis of Peak Signal to Noise Ratio (PSNR).

Keywords: Image Inpainting, Exemplar based, Texture synthesis, Image completion, Partial Differential Equation (PDE), Total Variation (TV).

1. Introduction

Completion of missing or damaged portions of images is ancient practice used extensively in artwork restoration. According to the category of image, this activity is also known as inpainting and texture synthesis, consists of filling in the missing areas or modifying the damaged ones in a manner non-detectable by an observer not familiar with the original images. The goal of completion varies, depending on the application, from making the completed area look consistent with the rest of the
image, to making them as close as possible to the original image. The applications of image completion consist of restoration of photographs, films, paintings, and removal of occlusions.

Bertalmio et al. [1] first presented the notion of digital image inpainting and used third order Partial Differential Equations (PDE) to propagate the known image information into the missing regions along the direction of isophote. Later [1], this inpainting approach was modified to take into account the Navier-Stokes flow [2]. This operation propagates information into the masked region while preserving the edges. So image inpainting is used to preserve edges across the missing regions, but when repairing large regions it introduces some blur easily.

Chan et al. present the Total Variation (TV) inpainting model in [9], based on the Euler–Lagrange equation, employs anisotropic diffusion based on the contrast of the isophote. This model, designed for inpainting small regions, does a good job at removing noise, but couldn’t repair large regions also. The Curvature-Driven Diffusion (CDD) model [4], extends the TV algorithm to also take into account geometric information of isophote when defining the ‘strength’ of the diffusion process, thus allowing the inpainting to proceed over larger areas. Although some of the broken edges are connected by the CDD approach, the resulting interpolated segments appear blurry. Because of PDE processes image only based on the local information, so when the target region is large or textured, the visual perception of the processed result is bad. PDE can not reconnect the linear structure in a large region and it can not restore texture patterns. There are many PDE based inpainting models [5-8], and all of these models are suitable for completing small, non-textured target region.

For textured images, image inpainting alone may not reconstruct the object faithfully, and a statistical or template knowledge of the pattern inside the missing area is needed as well. Natural images are composed of structures and textures, in which the structures constitute the primal sketches of an image (e.g., the edges, corners, etc.) and the textures are image regions with homogenous patterns or feature statistics (including the flat patterns). Pure texture synthesis technique cannot handle the missing region with composite textures and structures. Bertalmio et al. [11] proposed to decompose the image into structure and texture layers, and then repair the structure layer using diffusion-based method [1] and texture layer using texture synthesis technique [10]. It overcomes the smooth effect of the PDE-based inpainting algorithm; however, it is still hard to recover larger missing structures.

Many image inpainting schemes restore the holes in images by propagating geometrical structures into the missing region via diffusion, which is inspired by the partial differential equations of physical heat flow. The main drawback of these techniques is that the diffusion process introduces some blur, which becomes noticeable when filling larger regions. Exemplar-based image completion [12] is introduced to overcome this drawback and can produce a reasonably good quality of output for larger regions on images, which incorporates the advantage of image inpainting and texture synthesis.

The exemplar-based texture synthesis takes an exemplar and generates additional content based on that exemplar to create much more content than is contained in the exemplar. Traditionally, exemplar-based texture synthesis includes a correction process that compares neighborhoods of each synthesized pixel with neighborhoods of the exemplar.

Criminisi et al. [12] designed an examplar-based inpainting algorithm by propagating the known image patches (i.e., exemplars) into the missing patches gradually. To handle the missing region with composite textures and structures, patch priority is defined to encourage the filling order of patches on the structure. Wu [13] proposed a cross isophotes Examplar-based inpainting algorithm, in which a cross-isophotes patch priority term was designed based on the analysis of anisotropic diffusion. Wong [14] proposed a nonlocal means approach for the examplar-based inpainting algorithm. The image patch is inferred by the nonlocal means of a set of candidate patches in the known region instead of a single best match patch.

Zhaolin Lu [18] proposed a PDE-based image completion algorithm in which the geometrical property of an image structure is preserved. More examplar-based inpainting algorithms [15-17] were also proposed for image completion. Compared with the diffusion-based inpainting algorithms, the examplar-based inpainting algorithms have performed plausible results for inpainting the large missing image region.
2. Three Different Existing Exemplar Based Inpainting Algorithms
The following is a brief introduction of Criminisi et al.’s, Jiying Wu et al.’s and Zhaolin Lu et al.’s exemplar based inpainting algorithms, which are chosen to do some experiments on real scene images in section 4.

2.1. Antonio Criminisi et al.’s Exemplar Based Image Inpainting Algorithm
The core of this algorithm is an isophote-driven image-sampling process [12]. Antonio Criminisi et al adopt notation similar to that used in the inpainting literature. The region to be filled, i.e., the target region is indicated by $\Omega$, and its contour is denoted by $\delta\Omega$. The contour evolves inward as the algorithm progresses, and so we also refer to it as the “fill front.” The source region $\Phi$ which remains fixed throughout the algorithm, provides samples used in the filling process.

Figure 1: Structure propagation by exemplar-based texture synthesis

(a) Original image, with the target region $\Omega$, its contour $\delta\Omega$, and the source region $\Phi$.
(b) Synthesizing the area delimited by the patch $\Psi_P$ centered on the point $p \in \delta\Omega$
(c) The most likely candidate matches for $\Psi_P$ lie along the boundary between the two textures in the source region. e.g. $\Psi_{q'}$ and $\Psi_{q''}$.
(d) The best-matching patch in the candidates set has been copied into the position occupied by $\Psi_P$, thus achieving partial filling of $\Omega$.

We now focus on a single iteration of this algorithm to show how structure and texture are adequately handled by exemplar-based synthesis. Suppose that the square template $\Psi_P \in \Omega$ centered at the point P [Fig. 1(b)] is to be filled. The best-match sample from the source region comes from the patch $\Psi_q \in \Phi$, which is most similar to those parts that are already filled in $\Psi_P$. In the example in Fig. 1(b), we see that if $\Psi_P$ lies on the continuation of an image edge, the most likely best matches will lie along the same (or a similarly colored) edge [e.g., $\Psi_{q'}$ and $\Psi_{q''}$ in Fig. 1(c)]. All that is required to propagate the isophote inwards is a simple transfer of the pattern from the best-match source patch [Fig. 2(d)].

This algorithm is proposed for removing large objects from digital photographs. The result is an image in which the selected object has been replaced by a visually plausible background that mimics the appearance of the source region. It employs an exemplar-based texture synthesis technique modulated by a unified scheme for determining the fill order of the target region. Pixels maintain a confidence value, which together with image isophotes, influence their fill priority. The technique is capable of propagating both linear structure and 2 Dimensional (2D) texture into the target region with a single, simple algorithm.

The filling algorithm overcomes the issues that characterize the traditional concentric-layers filling approach and achieves the desired properties of 1) correct propagation of linear structures, 2) robustness to changes in shape of the target region, and 3) balanced simultaneous structure and texture propagation, all in a single, efficient algorithm.
Comparative experiments show that a simple selection of the fill order is necessary and sufficient to handle this task. It performs at least as well as previous techniques designed for the restoration of small scratches, and, in instances in which larger objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency.

2.2. Jiying Wu et al’s Exemplar Based Image Inpainting Algorithm

In [13] a hybrid image inpainting model is proposed. The hybrid model uses the Total Variation equation to decompose the image into a structure part and a texture part, and then more dynamic information is contained in the texture part. The structure part is inpainted by a bidirectional diffused PDE. The PDE restores image smoothly and preserves the linear structure. The texture part is processed by an exemplar-based model which is constrained by a cross-isophote diffused data term. It can find proper exemplars to fill in the target region and preserve linear structure. Two parts are combined after inpainting.

The model follows the basic concept in [3]. Image is decomposed into a structure part and a texture part. TV model is used to decompose the image, since the texture part generated by TV has a wider dynamic range. A morphological invariant bidirectional diffused PDE is used to inpaint the structure part. This PDE is derived based on the inviscid Helmholtz vorticity equation. The Helmholtz equation which is morphological invariant is a fluid dynamics equation. The equivalence between it and the inpainting PDE is proved in this paper. There is no error diffusion in bi-directional diffusion model and linear structure is preserved well by it. An exemplar-based inpainting model constrained by a cross-isophote diffused data term is used to inpaint the texture part. Data term is the absolute value of TV of pixel, and TV is morphological invariant. TV processes image conforms to geometry property. The linear structure part has higher inpainting priority, and a suitable exemplar is found.

A bi-directional diffused PDE is used to inpaint the structural part. There are both cross isophote diffusion and along isophote diffusion in this equation. The cross isophote diffusion item is 
\[
\nabla I / |\nabla I |
\]
and the along isophote diffusion item is 
\[
\nabla I / |\nabla I |
\]

The first task of the exemplar-based model is determining the patching priority. The priority is constrained by:
\[
P(\mathbf{p}) = C(\mathbf{p}) D(\mathbf{p})
\]
where \(C(\mathbf{p})\) is the confidence term:
\[
C(\mathbf{p}) = \sum_{q \in \Psi_p} \left( \frac{1}{\Psi_p} \cap (\mathbf{I} / |\nabla I|) \right) C(q) / |\Psi_p|
\]
where \(\Psi_p\) is the exemplar, \(|\Psi_p|\) is the area of exemplar, \(q\) is the pixel in exemplar \(D(\mathbf{p})\) is the data term. The absolute value of cross isophote diffusion TV is used as the data term.

Theoretical analysis and experiments proved that the hybrid model can be used to inpaint both texture and structure images well.
2.3. Zhaolin Lu et al’s Exemplar Based Image Inpainting Algorithm

Zhaolin Lu et al [18] presented a new approach based on exemplar-based completion model which combines the characters of inpainting and texture synthesis. The contributions of Zhaolin Lu et al’s approach consist of four aspects:

1) The size of image patch can be decided based on the gradient domain of image,
2) The filling priority is decided by the geometrical structure feature of image, especially the curvature and the direction of the isophotes,
3) It introduces a better patch-matching scheme, which incorporates the curvature and color of image,
4) The determined source template is copied into the destination template and the information of the destination template is updated.

The input of an image completion scheme is an image I which contains a manually masked area as the unknown region Ω (the region to be filled), while the output is a modified image I’ with Ω filled. Here, we conduct the similar notation as that used in [12]. We denote the unknown region by Ω, the known region by Φ, the contour of Ω by δΩ, the source and target patches by Ψ_p and Ψ_q respectively, gradient of image I on x and y coordinate by I_x, I_y respectively. The whole process of exemplar-based image completion is shown in figure 2.

![Figure 2: Exemplar-based Image Completion](image)

- a) Original image, with the target region Ω, its contour δΩ, and the source region Φ.
- b) Synthesizing the area delimited by the patch Ψ_p centered on the point p ∈ δΩ.
- c) The most similar candidate patch for Ψ_p lie along the isophote.
- d) Fill the Ψ_p with the most similar patch Ψ_q.

Image completion scheme is listed below.

1) Initialization;
2) Selecting a target patch Ψ_p with its center P ∈ δΩ and determining the size of Ψ_p adaptively;
3) Calculating the filling priority of Ψ_p and finding the most similar patch Ψ_q;
4) Filling the unknown pixels in Ψ_p from the corresponding pixels in Ψ_q;
5) Updating Ω, δΩ and G (…) until Ω to be null, if not, go back (2).

The basic unit of image completion is patch, which contains the structure and texture information of image. In [12], the size of image patch is fixed, which introduces some drawbacks. For example, if the patch is small, texel (unit of texture) is not thoroughly preserved, if it is too large, some tiny texel information will be lost. So in this paper, the size of patch is adaptively determined. First an original value is assigned to all patches, and then the size of each patch is determined by the local texture property in patch. The intention is to fill first those patches which have more of their pixels already filled.

Experiment results show that the algorithm succeeds in filling the target region without implicit or explicit segmentation of the image.
3. Evaluation Method
Formulating an accurate evaluation method for determining the success of the three algorithms was a very important yet difficult task. This was because no common method for evaluating inpainting algorithms has been presented in the literature. To try and provide a good and accurate evaluation of the algorithms, it was decided to use both a qualitative and a quantitative approach. The assessment of the results for the qualitative tests was done mainly by visual analysis.

The quantitative evaluation was performed by repeating the experiments multiple times for different size occlusions placed randomly throughout the images. These sizes were chosen as they show a large variation in occlusion sizes and would provide a good overview of the algorithm’s capabilities. This was obtained by calculating the peak signal-to-noise ratio (PSNR) between the two images. PSNR is “an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation”. PSNR values are represented in decibels (dB).

Basically the higher the PSNR value, the larger the similarity of the restored image to the original. Ideally it would be nice to specify what a good PSNR value is, but during the testing it was found that while some images could look visually pleasing, they may have extremely low PSNR values. The equation to calculate a PSNR value is given below:

$$\text{PSNR} = 20 \log_{10} \left( \frac{\text{MAX}_I}{\sqrt{\text{MSE}}} \right)$$

where $$\text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left\| I(i, j) - K(i, j) \right\|^2$$

and $$\text{MAX}_I = 255.$$ 

4. Analysis and Implementation of Experiment Results
We have experimented with the three methods on some images comparing with PSNR. These algorithms are programmed by matlab2008Ra and all experiments are run on a 2.93GHz PC.

Criminisi et al’s method [12] performs at least as well as previous techniques designed for the restoration of small scratches, and, in instances in which larger objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency.

The texture information is well restored and linear structure is preserved using the hybrid model proposed by Wu [13]. Theoretical analysis and experiments proved that the hybrid model can inpaint both texture and structure images well. The algorithm proposed by Zhaolin Lu et al [18] succeeds in filling the target region without implicit or explicit segmentation.

Fig.3 – fig.5 show the results produced by the aforementioned exemplar based Inpainting algorithms.

Figure 3 and Figure 4 are classical images used in many image restoration research papers. Figure 5 is a natural image from the internet. The images in each figure are arranged as original image, an image with occluded region, the final result of methods in [12], [13] and [18] respectively.
Figure 3: Reconstruction of lady occluded region of image. (a) Original Image. (b) The target region has been blanked out. (10% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al’s algorithm. (d) Reconstructed image using Jiying Wu et al’s algorithm. (e) Reconstructed image using Zhaolin Lu et al’s algorithm.

In Fig 3, the result images obtained by the three algorithms (c), (d) and (e), look visually pleasing but they have different PSNR values.

Figure 4: Reconstruction of man occluded region of image. (a) Original Image. (b) The target region has been blanked out. (12% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al’s algorithm. (d) Reconstructed image using Jiying Wu et al’s algorithm. (e) Reconstructed image using Zhaolin Lu et al’s algorithm.
Figure 5: Reconstruction of bird occluded region of image. (a) Original Image. (b) The target region has been blanked out. (8\% of the total image area). (c) The final image where the occluded area is reconstructed using Criminisi et al’s algorithm. (d) Reconstructed image using Jiying Wu et al’s algorithm. (e) Reconstructed image using Zhaolin Lu et al’s algorithm.

The tip of tree (in Fig 5 (c)) which is completed by [12] is obviously worse than other methods did.

During the testing it was found that while some images could look visually pleasing, they may have extremely low PSNR values.

Table 1: PSNR value for the three exemplar based image inpainting Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Lady occluded image</th>
<th>Man occluded image</th>
<th>Bird occluded image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criminisi et al’s</td>
<td>33.12</td>
<td>33.16</td>
<td>33.22</td>
</tr>
<tr>
<td>Jiying Wu et al’s</td>
<td>34.29</td>
<td>34.89</td>
<td>34.53</td>
</tr>
<tr>
<td>Zhaolin Lu et al’s</td>
<td>34.65</td>
<td>34.79</td>
<td>34.62</td>
</tr>
</tbody>
</table>

Table 1 shows the implementation results of the three exemplar based restoration methods proposed in [12], [13] and [18].

Graph 1: PSNR values of test images obtained by three exemplar based image inpainting methods
5. Limitations
Each of the algorithms presented here have a number of different problems and limitations. For example, Criminisi et al’s algorithm is capable of propagating both linear structure and 2D texture into the target region with a single, simple algorithm and has the limitations as 1) the synthesis of regions for which similar patches do not exist does not produce reasonable results 2) the algorithm is not designed to handle curved structures.

Jiying Wu et al’s algorithm works surprisingly well, yet it still has a problem of reconstructing the curved structure in the occlusion. Zhaolin Lu et al’s algorithm works well only if the missing region consists of simple structure and texture. If there are not enough samples in the image, it will be impossible to synthesize the desired image. In addition to these shortcomings, there are certain cases where the inpainting algorithms described here and in the literature would fail to successfully reconstruct the image.

6. Conclusion and Further Work
In this paper, we have looked at three different types of inpainting methods. For each of the algorithms, we have provided a detailed explanation of the process used for filling an occlusion making use of images and pseudo-code wherever appropriate. In addition, we have performed both a qualitative and quantitative analysis of the algorithms. From this analysis, a number of shortcomings and limitations were highlighted in relation to the type of information each algorithm can restore.

Compared with the other traditional inpainting algorithms, the exemplar-based inpainting algorithms have performed plausible results for inpainting the large missing region. But they work well only if the missing region consists of simple structure and texture. If there are not enough samples in the image, it will be impossible to synthesize the desired image. It shows that there is still a demand for an efficient image reconstruction method.

The digital inpainting problem is still far from being completely solved. Although a large number of algorithms exist that are capable of producing amazing results, they are usually limited to images that portray certain features. Overall, the implemented restoration methods also have some limitations for which more research needs to be done. It is hoped that the results obtained can provide a good framework for additional research that might be undertaken to improve upon the methods presented here. We plan to work for example on methods to restore complex structure information, such as corners, curves with large curvature, etc.

References
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