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Comparative Analysis and Evaluation of Image Imprinting 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. There are a large variety of image inpainting algorithms existing in the literature. They can broadly be grouped into two categories such as Partial Differential Equation (PDE) based algorithms and Exemplar based Texture synthesis algorithms. However no recent study has been undertaken for a comparative evaluation of these algorithms. In this paper, we are comparing two different types of image inpainting algorithms. The algorithms analyzed are Marcelo Bertalmio's PDE based inpainting algorithm and Zhaolin Lu et al's exemplar based Image inpainting algorithm. Both theoretical analysis and experiments have made to analyze the results of these image inpainting algorithms on the basis of both qualitative and quantitative way.

Keywords: Image Imprinting, Exemplar based, Texture synthesis, Partial Differential Equation (PDE).

1. Introduction

The concept of image inpainting has been around since the first inpainting algorithm proposed by Bertalmio et al (2000). Removing objects or portions of an image then filling in the missing data is a critical problem in photo-editing and film post-production, such as image restoration (e.g. scratch removal) and special effects (e.g. removal of objects). The goal of image inpainting 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 inpainting consist of restoration of photographs, paintings, films and completion of occluded regions.

There are two primary categories of the work that focus on missing image data recovery. One is the Partial Differential Equation(PDE) based inpainting techniques for filling in small image gaps and the other is an exemplar based texture synthesis algorithms for generating large image regions from sample textures.

2. Literature Review

There are a large variety of image inpainting algorithms found in the literature. The purpose of this paper is to introduce some of the inpainting algorithms that exist from the previous research into this area. We will group them into two broad categories such as PDE based and Exemplar based algorithms.

2.1 PDE based inpainting algorithms

Bertalmio et al (2000) 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. Many algorithms (C. Ballester et al (2001), M. Bertalmio et al (2001), M. Bertalmio et al (2000), T. Chan and J. Shen (2001), S. Masnou et al (1998)) address the region filling issue for the task of image inpainting where speckles, scratches, and overlaid text are removed. These image inpainting techniques are used to fill the holes in images by propagating linear structures into the target region via diffusion. They are inspired by the partial differential equations of physical heat flow and work convincingly as restoration algorithms. Their drawback is that the diffusion process introduces some blur, which becomes noticeable when filling larger regions.

Later Bertalmio et al (2000), this inpainting approach was modified to take into account the Navier-Stokes flow Bertalmio et al (2001). 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 (2000) present the Total Variation (TV) inpainting model in Levin et al (2003), 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 T. Chan and J. Shen (2001), 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.

There are many PDE based inpainting models (T.F. Chan et al (2002), T.F. Chan and J. Shen (2002), T.F. Chan Sung Ha Kang (2004), S. Esedoglu and J. Shen (2002)) and all of these models are suitable for completing small, non-textured target region. The PDE proposed by Marcelo Bertalmio (2006) is optimal in the sense that it is the most accurate third-order PDE which can ensure continuation of level lines. The continuation is strong, allowing the restoration of thin structures occluded by a wide gap.

Because of PDE based inpainting algorithms process the images only based on the local information, so when the target region is large or textured, the visual perception of the processed result is bad.

2.2 Exemplar based inpainting algorithms

A large number of exemplar based texture synthesis algorithms have been proposed that are based on the idea of creating an artificial texture from the source sample. 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).

One of the first attempts to use exemplar-based synthesis specifically for object removal was by Harrison (2001). There, the order in which a pixel in the target region is filled was dictated by the level of texturedness of the pixel's neighborhood.

Exemplar-based techniques which cheaply and effectively generate new texture by sampling and copying color values from the source were proposed by A. Efros and T. Leung (1999), M. Ashikhmin (2001), A. Efros and W. T. Freeman (2001), Freeman et al (2000) and A. Hertzmann et al (2001). Jia et al (2003) have presented a technique for filling image regions based on a texture-segmentation step and a tensor-voting algorithm for the smooth linking of structures across holes. Zalesny et al (2002) describe an algorithm for the parallel synthesis of composite textures.

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 (2004) designed an exemplar 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 (2006) 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 (2008) 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.

More exemplar-based inpainting algorithms (G. T. N. Komodakis (2007), I. Drori et al (2005)) were also proposed for image completion. Zhaolin Lu (2010) proposed an algorithm that copies the determined source template to the destination template and updates the information of the destination template.

All the aforementioned exemplar-based models used in image inpainting fills the target region with the most similar exemplar in image. The whole exemplar is copied into target region, so the texture information of image is well preserved. But they cannot preserve the linear structure well. These exemplar-based image completion algorithms 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.

3. Overview of Marcelo Bertalmio's PDE based inpainting algorithm and Zhaolin Lu et al's Exemplar based inpainting algorithm

Due to the large amount of previous research work, a large and variety of image inpainting algorithms exist. To try and cover all the algorithms available would be infeasible. With this in mind, we have decided to compare only two different algorithms. The first algorithm was the one that proposed by Marcelo Bertalmio in [2006] which focuses on reconstructing the structure of occluded area. The second algorithm was the one that proposed by Zhaolin Lu et al in [2010] which focuses on reconstructing the texture of occluded area.

The following is a brief explanation of Marcelo Bertalmio's PDE based and Zhaolin Lu et al's exemplar based inpainting algorithms, which are chosen to do some experiments on real scene images in section 5.

3.1 Marcelo Bertalmio's PDE based inpainting algorithm

In this paper a third-order PDE have been introduced to perform geometric inpainting on images. The image inpainting algorithm of Bertalmio et al (2000) is not contrast invariant, as it was pointed out by Chan et al (2001). In this paper (Marcelo Bertalmio (2006)), the inpainting problem was reformulated as a particular case of image interpolation in which the author intended to propagate level lines. Expressing this in terms of local neighborhoods and using a Taylor expansion, a third-order PDE was derived that performs inpainting. With this equation, the edges are propagated inside the gap with minimum bending, allowing for the connection of thin structures occluded by a wide gap, and also the formation of corners. This PDE is optimal in the sense that it is the most accurate third-order PDE which can ensure good continuation of level lines. The continuation is strong, allowing restoring thin structures occluded by a wide gap. The result is also contrast in-variant.

This algorithm performs well for small filling region images and preserves the linear structures.

3.2 Zhaolin Lu et al's Exemplar based inpainting algorithm

In this paper, the method by Criminisi et al (2004) was improved by the use of geometrical structure feature of image. The contributions of this new approach (Zhaolin Lu et al (2010)) consist of the following 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.

This algorithm performs well even for a large filling region images and for textured regions.

4. Evaluation Method

Formulating an accurate evaluation method for determining the success of the two 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:

$$PSNR=20.\log_{10}(MAX_I / \sqrt{MSE})$$

where $MSE= (1/ mn) \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \| I(i,j) - K(i,j) \|_2$

and $MAX_I = 255$.

5. Comparison of Experiment Results

We have experimented with the Marcelo Bertalmio's PDE based inpainting algorithm (2006) on some images comparing with Zhaolin Lu et al's Exemplar based inpainting algorithm (2010). We have implemented these algorithms using Mat lab 2008Ra.

Based on the experiment results obtained by the aforementioned algorithms, it is observed that PDE based inpainting algorithms cannot reconnect the linear structure in a large region and it cannot restore texture patterns. It is also observed that exemplar based inpainting algorithms can find proper exemplars to fill in the target region and preserve linear structure.

We have tested many input images and the experiment has been carried out multiple times for the same image with different occlusion sizes. Various parameter settings are needed for both algorithms.

The parameters needed for Bertalmio algorithm are: (1) I=No of inpainting steps needed to perform each iteration (2) D= No of Diffusion steps needed to perform each iteration (3) T= Total no of iterations to perform (4) dT=The speed of the evolution.

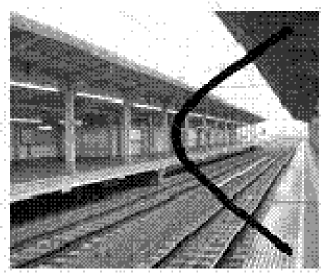
The parameters needed for Zhaolin Lu et al's algorithm are: (1) ω =template window size (2) β =Band size around the occluded area (3) ε =Error Threshold (4) $\delta\varepsilon$ = Multiplier for Error threshold if no progress is detected.

Sample results have been shown in the following figures.

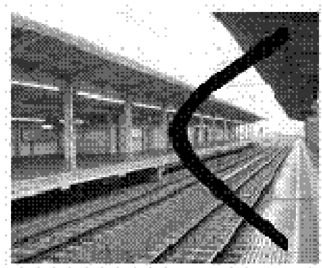
Figure 1: Results of two different inpainting algorithms (with variable occlusion sizes)

Original image with variable occlusion sizes

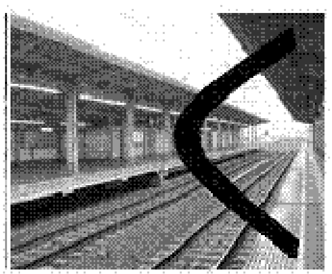
About 10 Pixels



About 20 Pixels



About 30 Pixels



1.2 Results of Marcelo Bertalmio Algorithm [12]

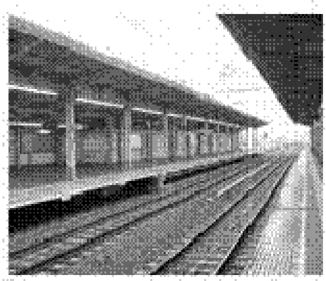
(a)

(b)

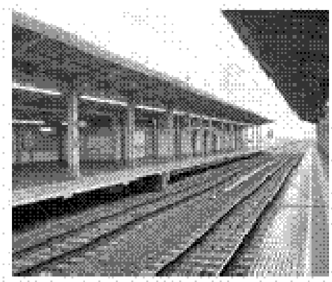
(c)

1.3 Results of Zhaolin Lu et al's Algorithm [21]

(a)



(b)



(c)

Figure 2: Results of two different inpainting algorithms

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Image with occlusion

Result of Marcelo Bertalmio [12]

Result of Zhaolin Lu et al [21]

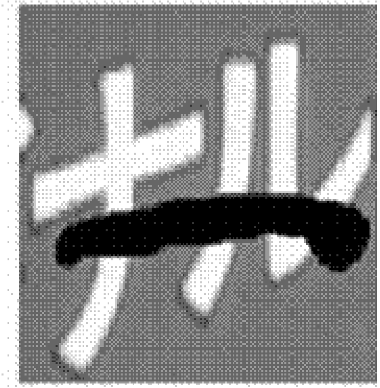


Image with occlusion

Result of Marcelo Bertalmio[12]

Result of Zhaolin Lu et al [21]

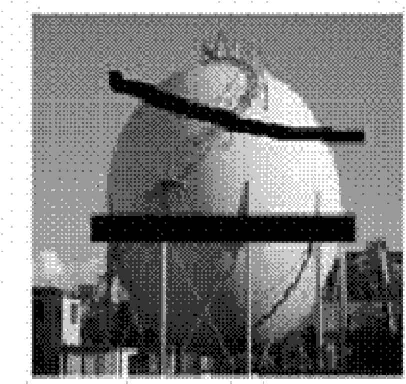
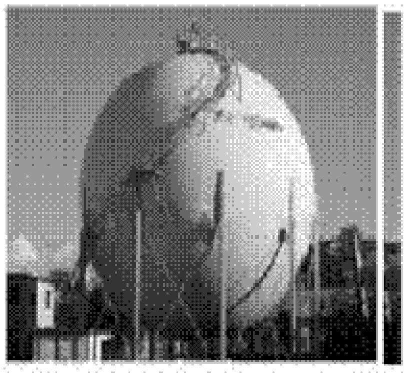
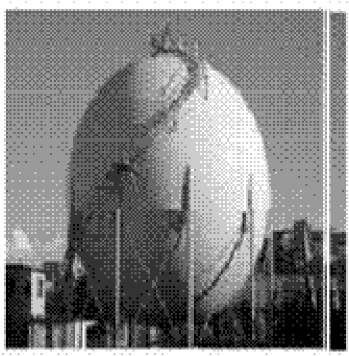


Image with occlusion



Result of Marcelo Bertalmio [12]

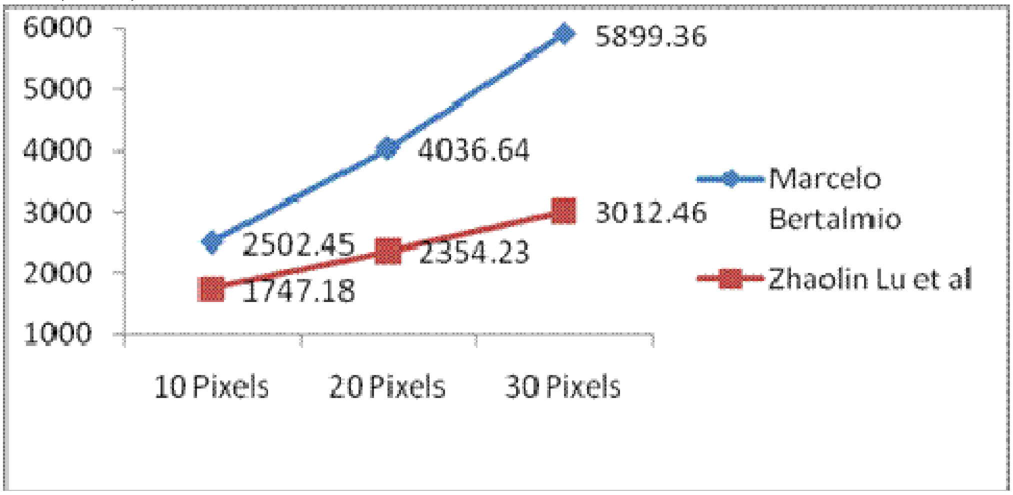


Result of Zhaolin Lu et al [21]

Table 1 Comparison of the two different inpainting algorithms

Inpainting Algorithms	MSE(10 ˜Pixels)	MSE(20 ˜Pixels)	MSE(40 ˜Pixels)
PDE based (Marcelo Bertalmio [12])	2502.45	4036.64	5899.36
Exemplar based (Zhaolin Lu et al's [21])	1747.18	2354.23	3012.46

Graph 1. The relationship between the value of MSE and the size of occlusion area.



From the experiment results it is known that exemplar based inpainting algorithm provides good results than PDE based algorithm in both qualitative and quantitative approach.

6. Conclusion and Further Work

In this paper, we have looked at two different types of inpainting methods. For each of the algorithms, we have provided a brief explanation of the process used for filling an occlusion making use of images. 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 PDE based inpainting algorithms, the exemplar-based inpainting algorithms have performed plausible results for inpainting the large missing region. Theoretical analysis and experiments proved that the exemplar based inpainting algorithms can inpaint both texture and structure image well.

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