Evaluation of Image Inpainting Algorithms

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Abstract- **Image inpainting is a technique to repair damaged images or to remove/replace selected regions. It was used to repair old artwork and also a part of movie special effects. This paper presents review of many successful algorithms for image inpainting which are Texture based algorithms, Diffusion(PDE) based algorithms, Exemplar and search based algorithms and Sparsity based algorithms. Here an evaluation of two classes of algorithms: Partial Differential Equations (PDEs) based algorithms and Exemplar-Based algorithms are presented. The results show the advantages and disadvantages.**

Index Terms- **Image inpainting, PDEs-based algorithm, Exemplar-based algorithm.**

I. INTRODUCTION

Image inpainting is the technique of filling in the missing regions of an image using information from surrounding areas. In image inpainting, the missing region is often referred to as hole, and is usually provided by the user in the form of mask or can be obtained by automatic or semi-automatic means. Some of the earlier nomenclature referred small region filling as inpainting and large area inpainting as image or video completion. In this work however, we do not make any such distinctions and these techniques are commonly referred as Digital Image and video inpainting algorithms. Digital inpainting has found widespread use in many applications such as removal of undesired objects and writings on photographs, restoration of damaged old paintings and photographs, transmission error recovery in images and videos, computer-assisted multimedia editing and replacing large regions in an image or video for privacy protection. The inpainting means a technique is to modify the damaged portion or region in an image or video. Then the inpainted region is undetectable to a neutral observer is described in [1]. The objective of image inpainting is to reconstitute the damaged portions or regions of the imge, then that image is more legible and restore its unity. Based on the context of operation, the goal of the inpainting can range from making the damaged image or video appear as close to the original to completely providing an alternate completion which is virtually unnoticeable to human observer.

Image inpainting is an ill-posed inverse problem that has no well-defined unique solution. To solve the problem, it is therefore necessary to introduce image priors. All methods are guided by the assumption that pixels in the known and unknown parts of the image share the same statistical properties or geometrical structures. The first category of methods, known as diffusion-based inpainting, introduces smoothness priors via parametric models or partial differential equations (PDEs) to propagate (or diffuse) local structures from the exterior to the interior of the hole. Many variants exist using different models (linear, nonlinear, isotropic, or anisotropic) to favor the propagation in particular directions or to take into account the curvature of the structure present in a local neighborhood. These methods are naturally well suited for completing straight lines, curves, and for inpainting small regions. These are not well suited for recovering the texture of large areas, which they tend to blur.

The second category of methods is based on the seminal work of Efros and Leung [2] and exploits image statistical and self similarity priors. The statistics of image textures are assumed to be stationary (in the case of random textures) or homogeneous (in the case of regular patterns). The synthesis is taken place by learning process for texture from the known part of the image or from similar regions in a texture sample. The Learning process is done by sequentially with starting of sampling, and by copying or stitching together patches (called examplar) taken from the known part of the image. The corresponding methods are known as examplar-based techniques. With the advent of sparse representations and compressed sensing, sparse priors have also been considered for solving the inpainting problem. The image (or the patch) is in this case assumed to be sparse in a given basis [discrete cosine transform (DCT), or wavelets]. Known and unknown parts of the image are assumed to share the same sparse representation. Examplar-based and sparse-based methods are better suited than diffusion-based techniques for filling large texture areas. Hybrid solutions have then naturally emerged, which combine methods dedicated to structural (geometrical) and textural components.

II. IMAGE INPAINTING TECHNIQUES

In this section, the different image inpainting techniques and corresponding approaches are explained.

A. Texture synthesis based inpainting

The texture synthesis based inpainting is one of the earliest modes of image inpainting methods. This method was use to complete the missing regions in general texture synthesis algorithms. The texture synthesis methods are use to synthesize new image pixels from an initial seed picture or video and strive to preserve the local structures

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of the image. To fill the holes by sampling and copying pixels from neighboring areas, earlier inpainting techniques utilized these methods only [2-7]. In [2], A Markov Random Field (MRF) is used for the synthesis of textures. This MRF method is used to model the local distribution of a pixel and new texture of the given image. It is synthesized by querying existing texture and finding all similar neighborhoods in the image. Their differences lay mainly in how continuity is maintained between the existing pixels and the inpainted hole. These querying synthesis based methods perform good only for a select set of images where completing the hole region with homogenous texture information would result in a natural completion.

Next this work was extended to a fast synthesizing algorithm[3]. In this algorithm, the new technique is introduced that is referred as image quilting. This technique is used to stitching together small patches of existing images. The authors, Heeger and Bergen was developed a new synthesizing technique i.e a parametric texture synthesis algorithm. This algorithm is used to synthesize a matching texture and given target texture [5]. This synthesis was done by matching the first order statistics of a linear filter bank. This filter bank roughly match to the texture discrimination capabilities of Human Visual System (HVS). Igehy et.al included a combined step to the above synthesis method to generate synthetic and real textures [7]. Yamauchi et.al introduced a multi-resolution texture synthesis method for image inpainting. This method can generate texture under varying brightness conditions[8]. Recently, Fang et.al introduced a fast multi-resolution based for image inpainting which is image completion based on texture analysis and synthesis[9]. In their method, a patch based method using Principal Component Analysis (PCA) was used to analyze the input image and to speedup the matching process a Vector Quantization (VQ) based technique was used for the texture inside the hole region. To create textures, so many texture synthesis methods discussed here and comparison taken place for different statistical characteristics of those methods and to generate textures under gradient, color or intensity variations. The texture synthesis based inpainting methods perform very well in approximating textures in the images. But these methods have difficulty in handling natural images as they are composed of structures in the form of edges. These methods have the problem of complex interactions between structure and texture boundaries. Sometimes they also require the user to mention what texture to be replaced. Hence we conclude that these methods can use to solve small subset of image inpainting issues only and these methods may not suitable for a wide variety of image inpainting applications.

B. Partial Differential Equation (PDE) based inpainting

Bertalmio et.al proposed a iterative algorithm which is based on Partial Differential Equation (PDE) [10] given the way for modern image inpainting. Figure 1 shows the result these algorithm for damaged images.

This iterative process propagates linear structures (edges) of the surrounding area by using the ideas of manual inpainting also called Isophotes, into the hole region denoted by Ω, using a diffusion process. This diffusion process is given by

$$I^{n+1}(i,j) = I^{n}(i,j) + \Delta t \cdot I_t^{n}(i,j), \forall (i,j) \varepsilon \Omega \quad \text{----}\ (1)$$

Where Δt is the rate of the change of inpainting, (i, j) are pixel co-ordinates, n is the iteration time, $I_t^n(i,j)$ is the update factor on the image $I^n(i,j)$.

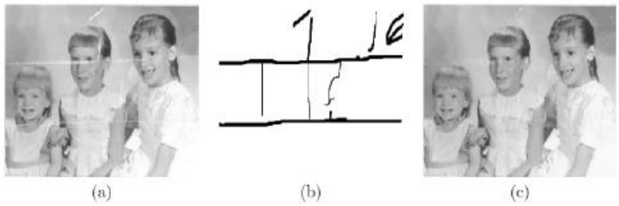

Figure 1: Digital image inpainting Example : (a) Original Image (b) Hole or Damaged regions in the form of mask. (c) The proposed algorithm Inpainted image in[10].

The Laplacian operation is applied to obtain a smoothed image update factor in the above equation in the direction perpendicular to the gradient in an iterative fashion. The following equation represents the PDE form of the above process.

$$I_t = \nabla(\Delta I).\nabla^{\perp} I \quad \text{---------}\ (2)$$

where $\nabla(\Delta I)$ is the Laplacian smoothness operation on the gradient and $\nabla^{\perp} I$ is the isophote direction. For the replication of large textured regions, this technique underperforms in due to blurring artifact of the diffusion process and this technique lack of explicit treatment of the pixels on edges of the images. This problem is treated as main drawback in this technique. Based in this work, the Total Variational (TV) inpainting model was proposed by Chan and Shen which uses Euler-Lagrange equation and anisotropic diffusion based on the strength of the isophotes [11]. Let E be the adjoining region and D be the inpainting region around the hole, a function u found by the variational inpainting model on the ex-tended inpainting domain adjoining the hole boundary $E \cup D$, such that under the denoising constraint on E, it minimizes a regularity functional $R(u)$. The function $R(u)$ is given below:

$$R(u) = \int_{E \cup D} r(|\Delta u|)dxdy \quad \text{------}\ (3)$$

where r is an appropriate nonnegative real function for nonnegative inputs.

This technique neither creates texture patterns nor connects broken edges. But it performs well for noise removal applications and small regions. The Total Variational (TV) model was extended to Curvature Driven Diffusion model (CDD) in [12]. This model included the curvature information of the isophotes to handle the curved structures in a better manner. The vector valued regularization under anisotropic diffusion framework was introduced by Tschumperle et.al [13] which one of the PDE based technique. Mainly these algorithms were focused on maintaining the correct structure of the inpainting area only and due to blurring artifacts these method could not perform as well in texture filling.

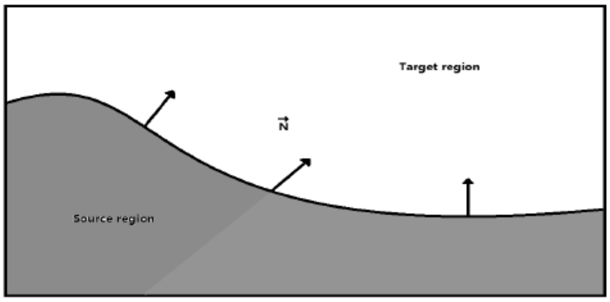

Figure 2: An image with source region, target region and vectors N. (By Sheng Li)

In Figure 2 gives the target region, source region and vectors. For propagate information from source region to target region, compute its change along the $\vec{N}$ directions. The $\vec{N}$ is the direction of smallest spatial change. Keep doing this, until reach the boundary of target region.

C. Exemplar and search based Inpainting

If the inpainting regions are large, then the mathematical method may not be suitable. So exemplar-based inpainting is the better choice for them. An algorithm based on texture-exemplar inpainting was introduced by Criminisi et al [14]. Extension of texture synthesis methods as a way to fill in large regions with pure textures repetitive two-dimensional textural patterns with some stochastically. There are some other algorithms for texture synthesis, such as, stochastic texture synthesis, pixel-based texture synthesis and patch-based texture synthesis. The damaged region is filled by copying color values from the neighborhood. Patch-based (exemplar-based) technique is a part of texture synthesis, it is more cheaper and effective than others. Criminisi et al [14] presents a novel and efficient algorithm that combines the "texture synthesis" algorithms generating image regions from sample textures and inpainting techniques that fill the small image gaps. This algorithm described as follows:

1. Determine the parameters of algorithm. A user selects a target region, Ω, to be restored. So the source region Φ is entire image minus the target region. Then the size of exemplar texture ψ. Those template textures called patches that contain a color value and a confidence value, which determines a pixel has been filled.
2. Compute patch priorities $P(p)$. The algorithm performs a best-first filling algorithm that determines the priority of every pixel. The priority is given as first the product of confidence term $C(p)$and second is data term $D(p)$.

1) $P(p) = C(p)D(p)$

2) $C(p) = \dfrac{\sum_{q\varepsilon\psi p\cap\Omega} C(q)}{|\psi p|}$

3) $D(p) = \dfrac{|\nabla Ip \cdot np|}{\alpha}$

3. Propagate texture and structure information. To find the best matches texture, the SSD (the sum of squared differences) of position of these patches is the measure. When the best one is found, propagate the information to the fill region.
4. Update confidence values. After filling the patch, the confidence of the patch is updated.

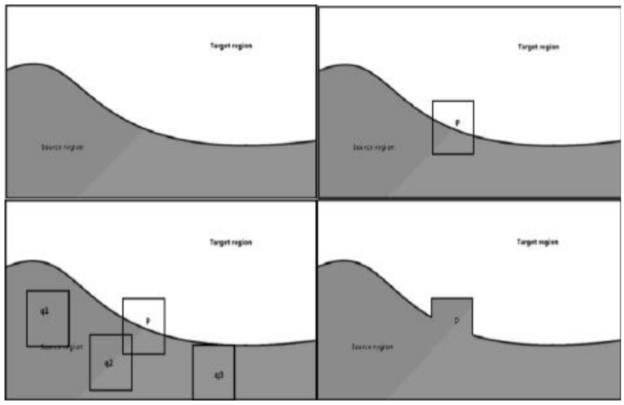

Figure 3: An example of exemplar-based algorithm. (By Sheng Li).

Figure 3 shows a single process of exemplar-based algorithm. The top-left one is the original image, the top - right one has a patch P. The bottom-left one has three patches P1, P2 and P3. In the bottom-right, the patch P be restored.

C. Patch Sparse Representation for inpainting

In this section ,we use a sparse linear combination of examplars to infer the patch in a framework of sparse representation to inpaint a selected patch on the boundary of missing region. Next, the regularization is taken place through linear combination of patches by the sparseness prior (regularization) on the combination coefficients. By this regularization technique only very few examplars contribute to the linear combination of patches with nonzero coefficients. This representation of patches is called patch sparse representation.

This sparse representation model extends the patch diversity. The patch diversity preserves texture without introducing smooth effect by sparseness assumption. Finally, the patch sparse representation and structure sparsity at the patch level constitute the patch sparsity. The patch structure sparsity is related to natural image which is inspired by the recent progress on the research of sparseness prior of natural image inpainting. However, it models the sparseness of nonzero similarities of a patch

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with its neighboring patches instead of high-frequency features.

The previous sparseness prior generally models the sparseness of image’s nonzero features, e.g., filter responses or gradients. This kind of method has been applied to the denoising of the image, super-resolution, inpainting, deblurring of the images and so on. The recent progress on sparse representation, which assumes that the image is represented by the sparse linear combination of an over-complete library of bases or transforms under sparseness regularization. This work has been widely applied to denoising of the images, recognition, edge detection, super-resolution, texture synthesis, etc., and finally achieves the performance of the state-of-the-art. In this work, the exampler- based inpainting method and sparse representation idea was combined under the assumption that the missing patch can be represented by the sparse linear combination of candidate patches. Then a optimization model is designed for patch inpainting for the given natural images.

D. Hybrid digital inpainting

In the hybrid digital inpainting the texture synthesis and PDE based inpainting methods are combined for completing the holes. The main idea behind these hybrid approaches is to decompose the image into separate texture region and structures. Then the corresponding decomposed regions are filled by texture synthesis techniques and edge propagating algorithms respectively[15-17]. If the fill region is large, then these algorithms are computationally intensive. The important direction for the general inpainting process is by structure completion through segmentation. This approach consists of two-stages: the first stage is the structure completion stage. In this structure completion stage, segmentation, using the algorithm of [19], is performed based on the insufficient geometry, color and texture information on the input and the partitioning boundaries are then extrapolated to generate a complete segmentation for the input using tensor voting [20] followed by texture synthesis. The second stage consists of synthesizing texture and color information in each segment, again using tensor voting.

III. RESULTS & COMPARISION

To compare PDEs algorithm and exemplar-based algorithm, the processing time, memory usage and the quality of result are three main aspects.All these three images, the two algorithms have been applied. For different image with different situation, the result shows the difference between those two algorithms. The A image has two different grayscale parts, the inpainting region is connection part. The B image is a wall with windows. The mission is repaired a half window. The last one C as the same as B, but the objective is to remove the window. The A image tested the inpainting of simple geometry image. The B image show the restoration of image with a complex background. The C image will be removed a big object with simple background.

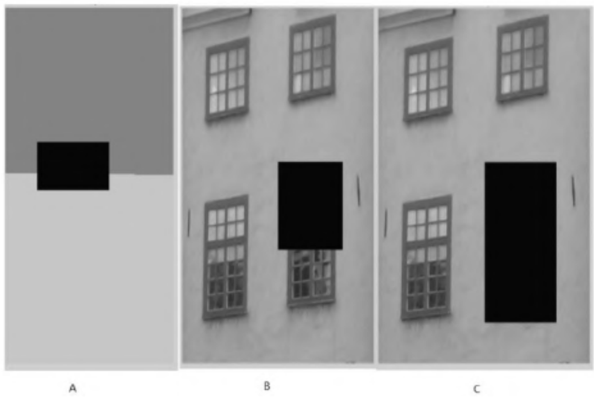

Figure 6: To be restored area of each image. (By Sheng Li).

TABLE I
INFORMATION OF INPAINTING IMAGE RESOLUTION AND TO BE RESTORED AREA.

	Resolution	Size to be Restored
A	200*400(80000) pixels	4505
B	503*491(246973) pixels	21033
C	503*491(246973) pixels	37349

The figure 7 shows the result of each algorithm. The a, b and c are implemented exemplar-based texture algorithm. The d, e and f are implemented PDEs algorithm. From the result, the exemplar-based algorithm can retouch the image. It can partly repair the image. But the c shows a drawback of exemplar-based inpainting. The PDEs algorithm looks like the blur of the image. But the f shows a good result. It is suitable for a narrow or small region filled and the object with a simple background deletion.

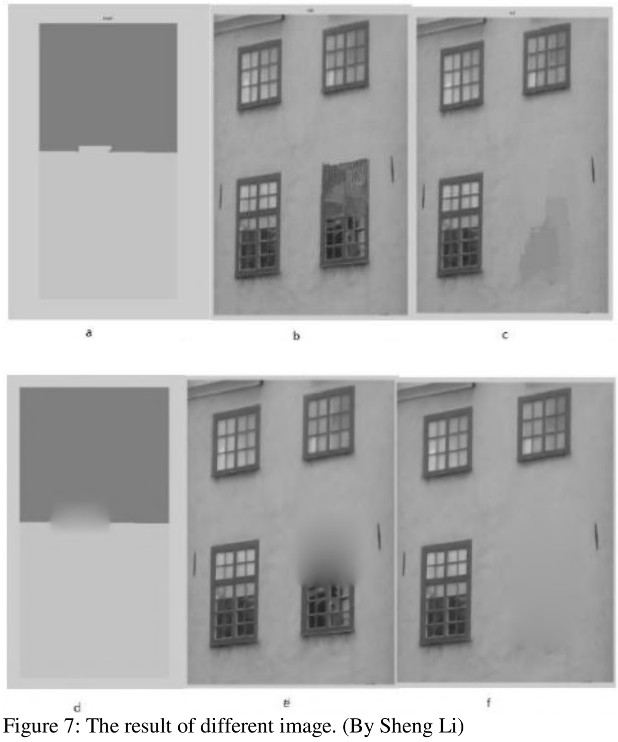

Figure 7: The result of different image. (By Sheng Li)

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TABLE II
THE PROCESSING TIME OF EACH IMAGE ON EACH INPAINTING ALGORITHM.

	A	B	C
Exemplar	8.90s	194.04s	390.09s
PDEs	0.34s	0.45s	7.42s

From the Table II, implemented different algorithm on the same image, the processing time of PDEs algorithm is faster than the exemplar, but the quality of exemplar is better than PDEs. With the target region increase and more complex, the exemplar based inpainting algorithm can get a better result than PDEs. But if the background of target region is simple, the PDEs get an ideal result. In my case, the PDEs algorithm is faster than exemplar-based algorithm. But the PDEs is an optimized MATLAB function. It is not fair for comparison. It gives us a future research: How to optimize the algorithm.

CONCLUSIONS

In this work, this paper just finds the suitable method. These inpainting algorithms are successfully restore the images. They are all suitable for small region inpainting. And the PDEs are good at remove object that if the background is simple. Otherwise, the result will looks like blurring. Exemplar-based inpainting algorithms are good at restoration of missing region. But the processing time is a problem. Too many computations on find the best matches patch. If the source region is larger, the time will be longer. If the source region is small, the quality of the result will be bad. The weakness of my exemplar-based inpainting algorithm is the choice of size of patches. If the size of source patch is too big, the best patch may not suitable. If otherwise, the size of source region is too small, the algorithm couldn't find the best match.

Though the exemplar-based algorithm is a suitable method, but it still needs to improve. If the image has a big resolution of 3264*1840, the processing time almost 10 minutes. So the algorithm is not yet suitable to implement on mobile device. It has to be suitable for today's mobile devices. For the PDEs algorithms, the processing is faster than texture algorithm, but it only suitable for narrow and simple region inpainting. When imply the algorithm on big region, the result looks like the blur of the region. But the algorithm would work on today's devices.

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