IMAGE INPAINTING

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ABSTRACT

Inpainting refers to the art of restoring lost parts of image and reconstructing them based on the background information i.e Image inpainting is the process of reconstructing lost or deteriorated parts of images using information from surrounding areas. In fine art museums, inpainting of degraded paintings is traditionally carried out by professional artists and usually very time consuming. The purpose of inpainting is to reconstruct missing regions in a visually plausible manner so that it seems reasonable to the human eye. There have been several approaches proposed for the same.

This paper gives an overview of different Techniques of Image Inpainting. The proposed work includes the overview of PDE based inpainting algorithm and Texture synthesis based inpainting algorithm. This paper presents a brief survey on comparative study of these two techniques used for Image Inpainting.

I. INTRODUCTION

Image inpainting refers to the process of filling-in missing data in a designated region of the visual input.The object of the process is to reconstruct missing parts or damaged image in such a way that the inpainted region cannot be detected by a causal observer. Image inpainting has been widely investigated in the applications of digital effect (e.g., object removal), image restoration (e.g., scratch or text removal in photograph), image coding and transmission (e.g.,recovery of the missing blocks), etc.

The most fundamental inpainting approach is the diffusion based approach , in which the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. These algorithms are well founded on the theory of partial differential equation (PDE) and variational method. The diffusion-based inpainting algorithms have achieved convincingly excellent results for filling the nontextured or relatively smaller missing region. However, they tend to introduce smooth effect in the textured region or larger missing region. The second category of approaches is the examplar-based inpainting algorithm. This approach propagates the image information from the known region into the missing region at the patch level. This idea stems from the texture synthesis technique proposed, in which the texture is synthesized by sampling the best match patch from the known region.

However, 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.* proposed to decompose the image into structure and texture layers, then inpaint the structure layer using diffusion-based method and texture layer using texture synthesis technique. It overcomes the smooth effect of the diffusion-based inpainting algorithm; however, it is still hard to recover larger missing structures. Criminisi *et al.*designed in [1]an exemplar-based inpainting algorithm by propagating the known 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-in of patches on the structure. Wu proposed a cross-isophotes exemplar-based inpainting algorithm, in which a cross-isophotes patch priority term was designed based on the analysis of anisotropic diffusion. Wong proposed a nonlocal means approach for the examplar-based inpainting algorithm. The image patch is inferred by the nonlocal means nof a set of candidate patches in the known region instead of a single best match patch. More exemplar-based inpainting algorithms were al so proposed for image completion.Compared with the diffusion-based inpainting algorithm, the exemplar-based inpainting algorithms have performed plausible results for inpainting the large missing region.

Most inpainting methods work as follows. As a first step the user manually selects the portions of the image that will be restored. This is usually done as a separate step and involves the use of other image processing tools. Then image restoration is done automatically, by filling these regions in with new information coming from the surrounding pixels (or from the whole image). In order to produce a perceptually plausible reconstruction, an inpainting technique must attempt to continue the isophotes (line of equal gray value) as smoothly as possible inside the reconstructed region.

In other words the missing region should be inpainted so that inpainted gray value and gradient extrapolate the gray value and gradient outside the region. The algorithms proposed for inpainting use the information from surrounding portions of image to inpaint the selected region. There are mainly three approaches for inpainting:

1. The first class of algorithms deals with the restoration of films. 2. Another class of algorithms deals with the reconstruction of textures in the image. 3. There is a third class of algorithms that deal with disocclusions. Presently there are different approaches to digital image inpainting and can be broadly classified into several different categories as listed below

I. Partial Differential Equation (PDE) based inpainting
II. Texture synthesis based inpainting
III. Exemplar and search based inpainting
IV. Hybrid inpainting
V. Semi-automatic and Fast Digital Inpainting.

In this section we will briefly explain the main ideas and the concepts of some of the existing inpainting algorithms.

II. METHODOLOGY

2.1 Partial Differential Equation (PDE) Based Inpainting

PDE(partial differential equations) is designed to connect edges or isophotes (line of equal gray values). Bertalmio et al.[11] proposed an image inpainting algorithm based on PDE. Its algorithm will have good results if missed regions are small, but in large damaged regions it will take so long time and wont have good results. Bertalmio et al. use similarities between image processing and fluid dynamic topics, and he proposed an image inpainting algorithm using the Navier Stokes equation. Chan et al. present several inpainting algorithms such as total variation (TV), curvature driven diffusion (CDD), and Euler's elastica. The authors try to minimize the TV-norm of reconstructed image in order to restore damaged pixels. Chan and Shen use energy functional involving the curvature of the level curves and tries to connect level curves in a smoothing fashion. Masnou and Morel in present a new model for image inpainting. They propose a simple but effective algorithm to connect level lines. Some works relate phase transition in supper conductors to image inpainting . Authors propose an algorithm that propagates tangential and normal vectors into missed regions then it reconstructs damaged image by fitting it to these vectors. Telea propose a fast marching method that can be considered as a PDE method which is faster and simpler to implement than other PDE based algorithms. All of above mentioned algorithms are very time consuming and have some problems with the damaged regions with a large size. PDE technique has been widely used in numerous applications such as image segmentation, restoration and compression. Even for traditional image inpainting.

2.2 Texture Synthesis Based Inpainting .

Texture synthesis based algorithms fill in damaged or missed regions using similar neighborhoods in an image, i.e. they try to match statistics of damaged regions to statistics of known regions in the neighbourhood of a damaged pixels. One of the earliest modes of image inpainting was to use general texture synthesis algorithms to complete the missing regions. The texture synthesis algorithms synthesize new image pixels from an initial seed and strive to preserve the local structures of the image. Earlier inpainting techniques utilized these methods to fill the holes by sampling and copying pixels from neighbouring areas. For example, Markov Random Field (MRF) is used to model the local distribution of a pixel and new texture is synthesized by querying existing texture and finding all similar neighbourhoods. Their differences lay mainly in how continuity is maintained between the inpainted hole and the existing pixels. These synthesis based techniques perform well only for a select set of images where completing the hole region with homogenous texture information would result in a natural completion.

Later this effort was extended to a fast synthesizing algorithm by stitching together small patches of existing images referred to as image quilting. Heeger and Bergen developed a parametric texture synthesis algorithm which can synthesize a matching texture, given a target texture. This was done by matching first order statistics of a linear filter bank which roughly match to the texture discrimination capabilities of Human Visual System (HVS). Igehy et.al included a composition step to the above method to generate synthetic and real textures . A multi-resolution texture synthesis method which can generate texture under varying brightness conditions was introduced for inpainting by Yamauchi et.al. Recently, a fast multi-resolution based image completion based on texture analysis and synthesis was introduced by Fang et.al. In their method, the input image was analysed by a patch based method using Principal Component Analysis (PCA) and a Vector Quantization (VQ) based technique was used to speedup the matching process of the texture inside the hole region. Various texture synthesis methods discussed here differentiate among themselves in their ability to create textures with different statistical characteristics and to generate textures under gradient, color or intensity variations. There are innumerable texture synthesis methods other than the aforementioned, but we shall restrict ourselves to illustrate those texture synthesis techniques specifiically used for inpainting. While the texture synthesis based inpainting perform well in approximating textures, they have difficulty in handling natural images as they are composed of structures in the form of edges and have complex interactions between structure and texture boundaries. In some cases, they also require the user to specify what texture to replace and the place to be replaced. Hence while appreciating the use of texture synthesis techniques in inpainting, it is prudent to understand that these methods address only a small subset of inpainting issues and are not suitable for a wide variety of applications.

2.3 Exemplar and Search Based Inpainting

The exemplar based approaches constitute an important class of inpainting algorithms and have proved to be very effective. An algorithm for handling large fill areas which combines the use of texture synthesis and Isophote driven Inpainting by a priority based mechanism in a unified framework was proposed by Criminisi et.al. In this algorithm the region filling order is determined by a priority based mechanism and is presented in Figure 1. Points which lie on the path of edges have a higher priority and hence are filled earlier than other pixels. Figure 1(b) shows a point P with high priority lying on the contour of the hole boundary. The neighbourhood or filled patch surrounding the highest priority pixel is then filled by finding the best matching patch in the known regions as explained in Figures 1(c) and (d).

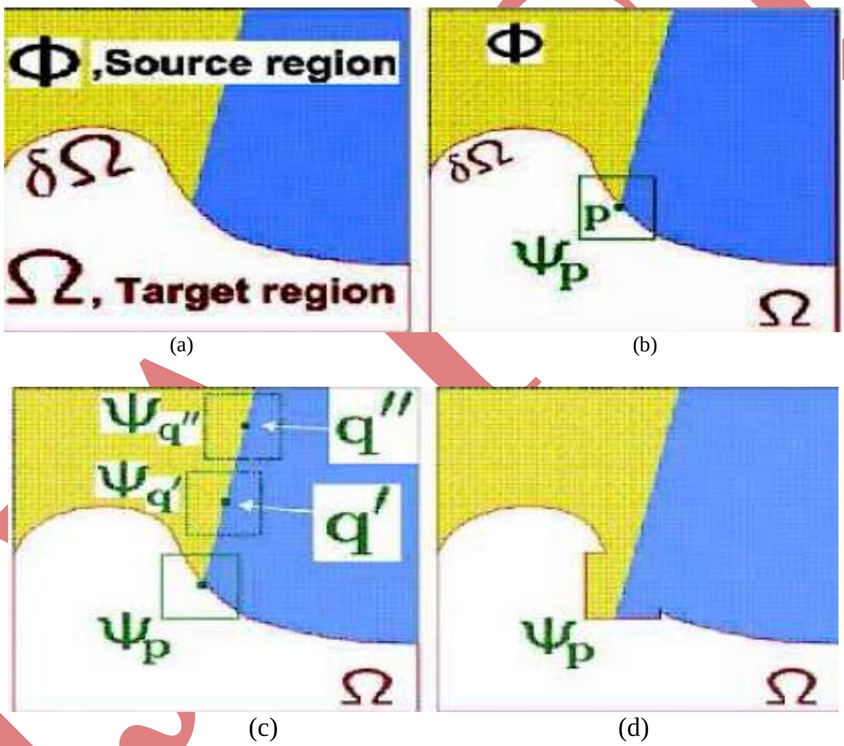


Figure 1: Exemplar based inpainting: fig a) Original image with target, its contour and source region. b) The filled patch marked by highest priority pixel. c) Most likely candidates for filling the patch. d) Pixel with highest priority is filled with the matching patch.

The patch size can be varied depending on the underlying characteristics of the image. This exemplar-based removal technique performs well for a wide range of images with good texture and structure replication but has some difficulty in handling curved structures. A major drawback of this exemplar method is the bias caused by selection of few incorrect patches in the priority based filling mechanism. These incorrect patches have a tendency to hijack the entire inpainting process by building upon the initial incorrect completions and have a spiralling effect that undermines the stability of the inpainting process. Recently, image inpainting techniques operated under the assumption that the information necessary to complete the hole is to be fetched from the regions outside the hole region of the same image. This work has opened new set ideas for image inpainting and produced promising image completion results over a wide variety of images. In this method, Gist, an image descriptor which characterizes the image using information in multiple frequency bands and orientation, is computed for every image in a database of over millions . The nearest semantic match for the image is obtained by searching through the entire database.

Once the match is obtained, the region inside the matching image is seamlessly blended into the source image using a poisson blending process . The result of applying this algorithm on a sample image with a large fill area is presented in Figure 2.

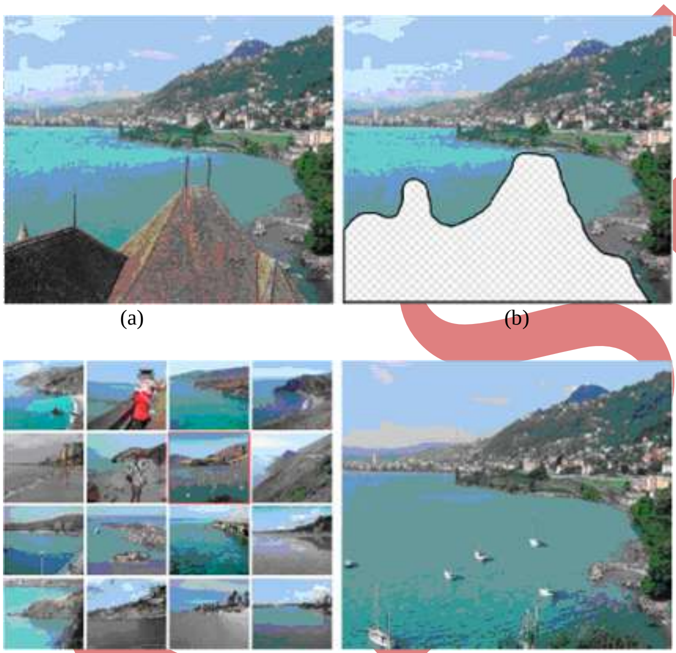


Figure 2: Search based inpainting: fig. a) Original image b) Image with a hole area marked by the user c) Results for the nearest semantic match using Gist of the image d) Completed image using Poisson blending.

2.4 Hybrid Inpainting

The hybrid approaches combine both texture synthesis and PDE based inpainting for completing the holes. The main idea behind these approaches is to decompose the image into separate structure and texture regions. The corresponding decomposed regions are filled by edge propagating algorithms and texture synthesis techniques. These algorithms are computationally intensive unless the fill region is small.One important direction we believe is more natural to the inpainting process is by structure completion through segmentation. An example of such an approach can be found in . It uses a two-step approach: the first stage is structure completion followed by texture synthesis. In the structure completion stage, a segmentation, using the algorithm of, is performed based on the insu±cient 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 . The second step consists of synthesizing texture and color information in each segment, again using tensor voting.

2.5 Semi-Automatic and Fast Digital Inpainting

Semi-automatic image inpainting with user assistance, in the form of guide lines to help in structure completion has found favor with researchers. The method by Jian et.al termed as inpainting with Structure propagation follows a two step process. In the first step a user manually specifies important missing information in the hole by sketching object boundaries from the known to the unknown region and then a patch based texture synthesis is used to generate the texture. The missing image patches are synthesized along the user specified curves by formulating the problem as a global optimization problem under various structural and consistency constraints. Simple dynamic programming can be used to derive the optimal answer if only a single curve is present. For multiple objects, the optimization is great deal more difficult and the proposers approximated the answer by using belief propagation

Depending on the size of the inpainting area, all the methods discussed above take minutes to hours to complete and hence making it unacceptable for interactive user applications. To speed up the conventional image inpainting algorithms, a new class of fast inpainting techniques are being developed. Oliviera et.al proposed a fast digital Inpainting technique based on an isotropic diffusion model which performs inpainting by repeatedly convolving the inpainting region with a diffusion kernel. A new method which treats the missing regions as level sets and uses Fast Marching Method (FMM) to propagate image information has been proposed by Telea. These fast techniques are not suitable in filling large hole regions as they lack explicit methods to inpaint edge regions. As a result, they introduce blur artifacts in these areas making the inpainting unsatisfactory.

III. IMAGE INPAINTING ALGORITHMS

3.1 PDE Based Inpainting Algorithm

A Partial Differential Equation (PDE) based iterative algorithm proposed by Bertalmio et.al [11] paved the way for modern digital image inpainting. The result of applying this algorithm to example images is shown in Figure 3. Borrowing heavily from the idea of manual inpainting, this iterative process propagates linear structures (edges) of the surrounding area also called Isophotes, into the hole region denoted by Ω using a diffusion process given by

$$I^{n+1}(i, j) = I^{n}(i, j) + \Delta t \,.\, I_t^{n}(i, j), \forall (I, j) \in \Omega$$

where n is the iteration time, (i, j) are pixel co-ordinates, Δt is the rate of the change of inpainting, I_t^n (i, j) is the update factor on the image I^n (i, j) . The update factor in the above equation, is a smoothed image obtained by applying a Laplacian operation in the direction perpendicular to the gradient in an iterative fashion. The PDE form of this processis expressed as

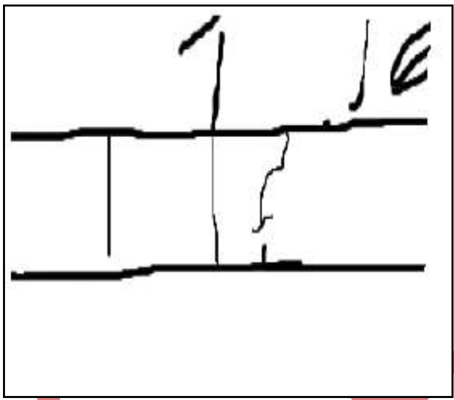
$$I_t = \nabla(\Delta I)\nabla^{\perp} I$$

where $\nabla^{\perp} I$ is the isophote direction and $\nabla^{\perp} I$ is the Laplacian smoothness of eration on the gradient. One of the main drawbacks of this technique is that it underperforms in the replication of large textured regions due to blurring artifact of the diffusion process and the lack of explicit treatment of the pixels on edges. Inspired by this work, Chan and Shen proposed the Total Variational (TV) inpainting model which uses Euler-Lagrange equation and anisotropic diffusion based on the strength of the isophotes. Let D be the inpainting region and E be the adjoining region around the hole, the variational inpainting model finds a function u on the extended inpainting domain adjoining the hole boundary *E U D*, such that it minimizes a regularity functional $R(u)$ under the denoising constraint on *E* defined below :

$$R(u) = \int r(|\nabla u|)\, dx\, dy$$

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

Fig 3: (a) Original Image



(b) Damaged regions or \hole" in the form of mask.

(c) Inpainted image

This technique performs reasonably well for small regions and noise removal applications but it neither connects broken edges nor creates texture patterns. The TV model was extended to Curvature Driven Diffusion model (CDD) in which included the curvature information of the isophotes to handle the curved structures in a better manner. Tschumperle et.al introduced another PDE based technique referred to as vector valued regularization under anisotropic diffusion framework. These algorithms were focused on maintaining the structure of the inpainting area and hence could not perform as well in texture flling due to blurring artifacts.

3.2 Texture synthesis based Inpainting Algorithm

Texture synthesis algorithms operate essentially on one pixel at a time and determine its value by looking for similar areas in the available image data. The fragment based algorithms can in some sense be considered as generalized texture synthesis. Instead of copying single pixels whole blocks are transferred into the inpainting domain thereby regarding that the resulting inpainting connects smoothly and is similar to the available image. Some hybrid algorithms which combine one or more techniques can also be used in inpainting domain .

In the following we give an overview on texture synthesis algorithms which have been used particularly for inpainting purposes:Cant & Langensiepen create copies of the image to be inpainted at various scales. In the coarsest image several candidates for a best matching patch are searched. In this search process also mirrored and rotated versions of the patches are considered. Once a set of candidate patch positions is found they are transferred to higher levels where the positions are adjusted to the finer resolution by searching in a neighborhood around the best positions found so far. Thus an exhaustive search has only to be performed at the coarsest level, on the finer levels only a small subset of the image has to be considered.

Criminisi et.al. and use a confidence and a priority function. The priority of a pixel depends on the confidence and on the gradient magnitude of its surrounding. Pixels lying close to convex corners inside the inpainting domain get high priority since they are surrounded by many high confidence pixels and thus can be reliably inpainted. On the other hand pixels lying close to edges (high gradients) are also assigned high priority such that edges are treated preferably. Continuation of edges tends to build concave spikes into the inpainting domain and the priority of the surrounding pixels decreases. Thus a balanced growing of edges and texture patches is guaranteed. Patches are taken to be fixed size and constant shape (i.e., no rotation or mirroring is considered) and the similarity of patches is simply calculated using sum of squared differences.

The edges as well as their influencing regions are readily restored by structure propagation. Then, in this subsection, the remainder unknown regions are treated as textural regions, so

texture synthesis is employed to fill-in these holes. For textural regions, we prefer patch-wise algorithms because they are good at preserving large-scale texture pattern.

We choose square patches as the fundamental elements while a confidence map is introduced to guide the order of synthesis. Unknown textural regions are progressively restored during texture synthesis by first reconstructing the prior patches and then the others that remain. The priority of a patch is determined by calculation of confidence and the distance from the edge.

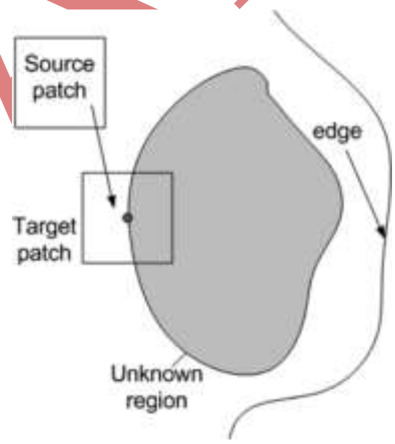


Fig..4. Patch-Wise Texture Synthesis in Our Scheme.

As shown in Fig.4, for each patch centered at a marginal pixel of unknown regions (denoted by target patch), we calculate the average confidence value of all pixels in this patch, as well as the average distance of all pixels from the edge. Then the patch with the highest confidence rating and the greatest distance from the edge will be synthesized first.

Afterwards, a source patch, which is most similar to the target patch, will be searched out from the neighbourhood of the target patch. Here, the similarity of two patches is measured by the SSD of pixel values between overlapped available pixels of two patches. A patch that results in the least SSD will be chosen as the source patch. Notice that the filling-in process is not as simple as copy-paste work, we have to deal with overlapped regions as well as seams. In our algorithm, the graph-cut method is used to merge the source patch into the existing image, and the Poisson editing is utilized to erase the seams. After one patch is restored, the confidence map is updated. All newly recovered pixels are treated as available pixels in the following synthesis steps. Then, the next target patch is searched and processed until no unknown pixel exists.

IV CONCLUSIONS

In this review, we have discussed the existing techniques of Image Inpainting. We also presented PDE based Inpainting Algorithm and Texture synthesis based Inpainting Algorithm.. By applying these algorithms to the various images it is found that the choice of using Texture or PDE algorithms depends on the nature of the image to be inpainted. The PDE algorithm is used for structure dominated images to fill-in narrow or crack type regions, while the texture algorithm is more suited for textured images. The time required for the inpainting process depends on the size of the image and the regions to be inpainted, and it ranges form few seconds to several minutes for large images.

This comparison indicates as expected that the PDE-based digital inpainting algorithm has some disadvantages, which can be summarized as follows:

• Resulting image is blurred.

• Large textured regions are not well reproduced.

Also the texture Exemplar-based inpainting algorithm fails in some cases, and that is because:

• The algorithm can not accurately propagate image structures.

• The matching criterion for texture synthesis that only uses only the color information produced artifacts in the image.

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