An Effective and Efficient Technique of Image Inpainting: A Review

Poonam A. Domadia
P. G. Student
Department of Computer Science
Parul Institute of Technology, Vadodara, Gujarat

Pankaj Kumar Gautam
Assistance Professor
Department of Computer Science
Parul Institute of Technology, Vadodara, Gujarat

ABSTRACT
Today in this digital world Image Inpainting is the emerging field in the area of Image Processing. Its main goal is to restoring missing or damaged areas in an image. This field of research has been very active over recent decade, and its enhanced by application such as renovating image from scratches or text overlaps, to improve lost part of the images, to remove object and fill the region and these all are used in the images which are captured by cameras and other capturing devices also. In inpainting that has no well-defined unique solution but that has different types of method like diffusion based method, examplar based method, global method.

Keywords
Inpainting, Diffusion-based, Examplar-based, Global/Hybrid Method.

1. INTRODUCTION
Inpainting, a set of techniques for making undetectable modifications to images, is as ancient as art itself [1].It has no unique solution therefore to solve the problem it is necessary to introduce image priors. In this all methods are work on pixels in the known and unknown parts of the images. Images share the same statistical properties or geometrical structures. This assumption translates into different local or global priors, with the goal of having an inpainted image as physically likely and as visually pleasing as possible.

There have been many research for the Inpainting and are classified into two major categories. An overview of these methods is found in [4-6]. First category of methods is diffusion based inpainting. Its introduce smoothness prior using partial differential equations (PDE) to diffuse local structure from the external to the internal of the hole. These methods are naturally well suited for completing orthodox lines, curvatures, and for inpainting small areas. Second one is examplar based inpainting method. This method is based on seminar work of Efros and Leung [2]. The statistics of image textures are assumed to be stationary for random texture or homogeneous for regular patterns. The texture to be synthesized is learned from the same regions in a texture sample or from the known part of the image. Learning is done by sampling, and by copying or stitching together patches taken from the known part of the image [3].

Examplar based method is well suited than diffusion based method for filling large texture regions.

The Classification of the Image Inpainting methods is as shown in table 1. This review or survey identified only theoretical knowledge of different kind of methods for inpainting.

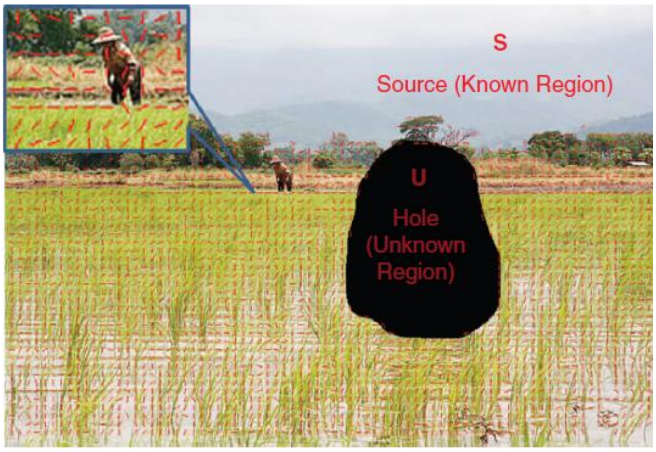

Fig 1: Identified known and unknown region of image[3].

2. DIFFUSION BASED INPAINTING METHOD
The term diffusion comes from the idea of propagating local

information with smoothness constraints, by analogy with physical phenomena like heat propagation in physical structures[3].

An image **I** can be mathematically defined as

$$I : \begin{vmatrix} \Omega \subset R^n \to R^m \\ X \to I(X), \end{vmatrix} \quad (2.1)$$

Where, x represents a vector indicating spatial coordinates of a pixel $p_{\mathbf{x}}$, which in the case of a 2-D image (n = 2), is defined as x = (x, y). In the case of a color image, each pixel carries three color components (m = 3) defined in the (R, G, B) color space. Each c^{th} image color channel of I is denoted $I_c : \Omega \to R$. I is the input image, $\Omega = S \cap U$, S is the known part of the I and U is the unknown part of I which is used to inpaint.

The first step is to retrieve the local image geometry and then use PDEs to describe continuous evolutions of the image and of its structures.

2.1 Retrieving Image Local Geometry
Local geometry is retrieved by computing isophotes or structure tensors. Isophotes are lines of constant intensity within the image (as shown in figure 1 by red lines) and its direction at given pixel p_x are normal to discretized gradient vector computed at this point, and its denoted by $\nabla I^{\perp}$.

Table 1. Classification of Inpainting Methods[3]

Features	Diffusion based	Examplar based	Hybrid Method	Global
Priors	Smoothness	Sparsity, Self-similarity	Smoothness, Similarity	statistical, low rank
Optimization	Greedy	Greedy/Global	Greedy/Global	Global
Sensitivity to setting	Low	High	High	High
Holes	Small	Medium to Big	Medium to Big	Small to Medium
Application	Restoration	Restoration, Editing, Concealment	Restoration, Editing, Concealment	Restoration

Another method used to retrieve local geometry is centered on the computation of the spectral elements of the structure tensors, also called as Di Zenzo matrix [7]. The structure tensor for a scalar image is computed at each point p_x as $G = \nabla I \nabla I^T$, where the term ∇I is the image spatial gradient, and the term ∇I^T is the transpose of the image gradient[3].

By using the spectral decomposition, the structure tensor G can be expressed as G = RDR^T, where the columns of R are the eigenvectors v1 and v2 of G and D is the diagonal matrix and its values are the corresponding eigenvalues m1 and m2. The orientation of the eigenvector **v**2 corresponding to the smallest eigenvalue *m*2 is the orientation with the lowest variations. The orientation of the eigenvector v1 corresponding to the highest eigenvalue *m*1 gives the gradient direction. The retrieved local image geometry can be used to control directions along which pixel values are propagated in the inpainting process.

2.2 Inpainting using Diffusion PDEs

The use of regularization or diffusion for image inpainting was established by Bertalmio et al. [1] in 2000.The PDE-based regularization methods that are isotropic and anisotropic are used for inpainting. In [1] author use an anisotropic model that propagates image Laplacians as expressed by (2) from the surrounding neighborhood into

the interior of the hole.

$$\frac{\partial I}{\partial t} = \lambda_1 I_{v1v1} + \lambda_2 I_{v2v2} \qquad (2.2)$$

Where, the terms I_{v1v1} and I_{v2v2} are the image Laplacians, i.e., the second derivatives of I in the directions given by the vectors v1 and v2 are derived from the local image structure. The diffusion is controlled by the knowledge of the smoothing directions v1 and v2, and the respectively weights m1 and m2.

The directions of the propagation are given by the directions of the isophotes estimated by the perpendicular to the image gradient in each point [3]. The algorithm numerically solves the equation as follow

$$\frac{\partial I}{\partial t} = \nabla(\Delta I)\nabla I^T \qquad (2.3)$$

for the image intensity I inside the hole, until a steady state solution $(\nabla(\Delta I)\nabla I^T = 0)$, which means that the image Laplacians ΔI remain constant in the directions $\nabla I^{\perp}$ of the isophote. The term $\nabla(\Delta I)\nabla I^T$ is the derivative of ΔI in the direction $\nabla I^{\perp}$ leading to a smooth continuation of available information inside the region to be inpainted. The analogy between this propagation of image intensity along smooth level curves and the transport of vortices in fluid dynamics formalized with the Navier–Stokes equations has been established in [8].

PDE-based methods require implementing iterative numerical methods that are generally quite slow. A fast marching technique is described in [9], which estimates the unknown pixels in one pass using weighted means of already calculated pixels. A trace-based PDE model is proposed in [10] to regularize multivalued images. It was observed in [10] that Gaussian performance inherent to the use of tensors for defining orientation and strength of the diffusion degrades the reconstruction of curvature image structures like corners. This observation directed the author in [10] to use heat flows constrained on integral curves to better preserve curvatures in image structures.

Diffusion methods tend to extend structures arriving at the edge of the area to be filled in. These methods are hence successful for piecewise smooth images, for propagating strong structures, or for filling small holes. However, they are not appropriate for textured images, especially if the region to be filled is large. Although intended to preserve edges, after a few diffusion iterations, the inpainted region appears smooth with lots of blur when the missing region is large.

The researchers get some of the results as shown in figure 2. Figure 2 shows inpainting results after a few iterations when using two different diffusion equations: isotropic diffusion with heat equation, and edge-enhancing diffusion (EED) [11].Isotropic diffusion introduces a blur over the entire region to be filled in.

3. EXAMPLAR-BASED INPAINTING METHOD

Another category of the inpainting method is appeared in the last era based on seminar work on texture synthesis [2], [12] with goal of better recovering the texture of the missing region. The goal of texture synthesis is to create a texture from a given sample like that the created texture is larger than the source sample with a similar visual appearance.

Examplar-based inpainting has been for a large part, inspired by local region-growing methods that grow the texture one pixel or one patch at a time, while maintaining coherence with nearby pixels.

Fig 2: Diffusion process with isotropic diffusion after (a) 10, (b) 20, and (c) 600 iterations [3]. Edge enhancing diffusion [11] after (d) 10, (e) 50, and (f) 600 iteration [3].

Most of the pixel based synthesis techniques depend on Markov Random Field(MRF) modeling of texture. Instead of running a complex probabilistic inference on the graphical model of the MRF for learning the missing pixels from the input sample, simpler, yet efficient, approximate solutions have been proposed in [2]. Texture synthesis methods directly apply to the inpainting problem where the known part of the image can be seen as the input texture sample from which the missing pixels can be learned.

The pixel-based texture synthesis technique in [2] proceeds as follows. Let p_x be a pixel located at position x in the image I , and ψ_{p_x} be the patch centered on the pixel p_x. This patch has a known part and an unknown part. The idea is to search for the patch ψ_{p_j} the most similar to the input patch ψ_{p_x}. The central pixel p_j having a neighborhood most similar to the known neighborhood of p_x is then copied to recover p_x. Image information is therefore pixel-per-pixel propagated from the known part to the unknown part of the image. This pixel-per-pixel algorithm suffers from a high computational cost, even if its complexity can be reduced by constraining the search for best matching patches among the candidates of the neighboring pixels that have been already inpainted [13]. The pixel-based synthesis techniques often suffer from synthesis errors propagation and from repetitive patterns, which look unnatural especially in the case of stochastic textures.

Approaches synthesizing entire patches rather than only one pixel at a time have then emerged to cope with the drawbacks just mentioned. Instead of synthesizing the missing region pixel per pixel, the idea of patch-based solutions is to recover entire patches in one step by sampling and copying texture patterns from the source [14]. The examplar-based inpainting mostly refers to these methods that synthesize entire patches by learning from patches in the known part of the image. Since they synthesize entire patches at once, these methods are faster than pixel-based.

Criminisi et al [15] designed an exemplar based inpainting algorithm by propagating the known image patches (i.e., exemplars) into the missing patches gradually. The method of Wexler et al [16] may also be considered as a global optimization, it is defined and computed in an entirely different way, and it gives significant different behavior in difficult inpainting examples.

To improve the effect of results, Sun and Xu [17] proposed a patch selection method by structure sparsity and a patch propagation method by sparse representation. Wohlberg [18] proposed a competitive filling order estimating method by joint optimization of linear combinations of exemplars. Zhaolin Lu [19] proposed a PDE-based image completion algorithm in which the geometrical property of an image structure is preserved.

The examplar based method follows the 2 steps as described in [15]: the filling order computation and the texture synthesis.

3.1 Patch Priority

The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. Classically, a high priority indicates the presence of structure. The priority of a patch centered on p_x is just given by a data and confidence term. Regarding the data term, a tensor-based [20] and a sparsity-based [17] data terms have been used.

Tensor based priority term is based on a structure tensor; this is given by:

$$J = \sum_{i=1}^{m} \nabla I_i \nabla I_i^T \qquad (3.1)$$

J is the sum of the scalar structure tensors $\nabla I_i \nabla I_i^T$ of each image channel I_i (R,G,B). The tensor can be smoothed without cancellation effects: $J_\sigma = J * G_\sigma$ where $G_\sigma = 1/2\pi\sigma^2 \exp(-(x^2+y^2)/2\sigma^2)$, with standard deviation σ. The main advantages of a structure tensor is that a structure coherence indicator can be deduced from its eigenvalues[21]. A data term *D* is then defined as [22]:

$$D(p_x) = \alpha + (1-\alpha)\exp\left(-\frac{\eta}{(\lambda_1 - \lambda_2)^2}\right) \qquad (3.2)$$

Where η is a positive value and $\alpha \in [0, 1]$ ($\eta = 8$ and $\alpha = 0.01$). On flat regions ($\lambda 1 \approx \lambda 2$), any direction is favoured for the propagation (isotropic filling order). When $\lambda 1 >> \lambda 2$ indicating the presence of a structure, the data term is important.

The sparsity-based priority has been proposed recently by

Xu et al. [17]. In a search window, a template matching is performed between the current patch and neighbouring patches that belong to the known part of the image. By using a non-local means approach [23], a similarity weight $w_{px,pj}$ is computed for each pair of patches.

3.2 Texture Synthesis

The filling process starts with the patch having the highest priority. To fill in the unknown part of the current patch *ψuk*

*p***x** , the most similar patch located in a local neighbourhood *W* centered on the current patch is sought. A similarity metric is used for this purpose. The chosen patch *ψ∗ p***x** maximizes the similarity between the known pixel values of the current patch to be filled in *ψk p***x** and co-located pixel

values of patches belonging to *W*:

$$\Psi^*_{p_x} = \arg\min_{\Psi_{pj} \in W} d(\psi^k_{p_x}, \psi^k_{p_j})$$
$$Coh(\psi^{uk}_{p_x}) < \lambda_{coh} \qquad (3.3)$$

where *d(.)* is the weighted Bhattacharya used in [24]. *Coh(.)* is the coherence measure initially proposed by Wexler *et al*. [16]:

$$Coh(\Psi^{uk}_{p_x}) = \min_{p_j \in S}(d_{SSD}(\psi^{uk}_{p_x}, \psi^{uk}_{p_j})) \qquad (3.4)$$

where *d*SSD is the sum of square differences. The coherence measure *Coh* simply indicates the degree of similarity between the synthesized patch $\psi^{uk}_{p_x}$ and original patches. So the constraint in equation (2.3) prevents pasting in the unknown regions a texture that would be too different from original textures. If none of the candidates fulfill the constraint (2.3), the filling process is stopped and the priority of the current patch is decreased. The process restarts by seeking the patch having the highest priority. It is interesting to note that a current study [25] uses a similar term to predict the quality of the inpainting.

4. APPLICATION OF IMAGE INPAINTING

The problem of inpainting is encountered in various image processing applications: image restoration, editing disocclusion in image-based interpretation, interpolation, recover lost data of image, texture synthesis or image resizing. Inpainting has also been considered in the context of lossy image compression. It can be used in cinema and photography for "restoration", for removing effects like scratches, dust spot from images. It can also be used for removing some object from image or removing red eye removal and also to remove symbols and signs in videos. The goal here is not to assess or benchmark in terms of inpainting results the numerous methods which exist, nor to give an complete list of all potential applications. It is instead to illustrate the main applications with some examples of algorithms. These all algorithms are not fulfilling all the requirement of the application. There are some of the limitations for inpainting.

5. CONCLUSION

Image Inpainting has acknowledged a lot of attention in the last some of decade. In the old era human are not recover the old photographs and cinema videos but now by using this image inpainting method we can do this fast. Different kind of approaches have been proposed with varying applicability in restoration, object removal, and in texture synthesis. Inpainting algorithm are limited at a particular level for the video editing such as for moving object in video and sometimes cause of the camera motion therefore inpainting is difficult. From these all techniques examplar based method is better as compare to others. And further we can work on images which have large region to fill.

From the last some of the era researcher invent different types of technique and enhance image visually pleasing and physically plausible.

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