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A Survey on Different Techniques and Algorithms for Image Inpainting

[1]Hinal Patel, [2]Alka Patel

[1] Final Year Student of ME (IT), L. D. College of Engineering, Ahmedabad, Gujarat, India

[2]Assistant Professor, L. D. College of Engineering, Ahmedabad, Gujarat, India

Abstract: The process of restoring missing or deteriorated regions in an image is called an Image Inpainting. The purpose of digital image inpainting is to reconstructing the loss information according to surrounding image information and to get rid of larger objects from them. The target of image inpainting is to modifying the digital image in an undetectable manner that the changes are invisible to an observer. Image inpainting has various applications such as restoration of older films, removal of objects, red-eye correction, and removal of text. This paper critically examines and reviews methods of Image Inpainting algorithm such as Exemplar based, Diffusion-Based, Partial Differential Equations (PDE) based, Texture based and Hybrid based**.**

***Index Terms* - Image Inpainting, Object removal, Image reconstruction, Structure, Texture.**

I. INTRODUCTION

In recent years, digital image inpainting is one of the interesting research topics within the field of image processing. The Image Inpainting method originally needed human artists to restore the images by hand. But in recent time researchers have present various automatic digital image inpainting methods. The aim of image inpainting is to modifying the digital image in an undetectable manner that the changes are invisible to an observer. The digital inpainting is easy and intuitive, which mostly depends on how the inpainting algorithm uses the existing part of the image (i.e. the source regions information) for filling the holes (i.e. the target region) in the image. The automating process reduced the interaction required by the user. The only action required by the user is the selection of the source image to be inpainted. The process of Image Inpainting follow four steps: (i) Read a damaged image and its mask image, the mask image is an image that shows the pixel intensity value one for the missing region and value zero for the available region. (ii) The structure of the surrounding neighbors of the missing region is continued into the gap, contour lines are drawn via the elaboration of these incoming at the boundary of the gap (iii) The various regions within the gap are then filled with color. (iv) The tiny details are painted, i.e. texture is added. Image Inpainting has a range of applications such as scratch removal of digital photos and old films, removal of text like dates, subtitles, and logos. Current applications include special effects such as objects removal, removing redeye, images and video compression, image coding and decoding, zooming, super resolution, and 3D reconstruction

II. BACKGROUND

There are three main categories of 2D image inpainting algorithms.

1) Structural inpainting
2) Textural inpainting
3) Combination of Structural and Textural Inpainting.

All these inpainting methods use the neighboring region information in order to fill the missing or damaged region, similar to how physical images are restored. The structure depends on the arrangement of interrelated elements like edges and corners. For example, most houses or buildings in images have rectangular outlines and sharp edges. In structure inpainting to reconstruct the images, it uses information that comes from the neighboring pixels and edges available in the image. The texture gives information about color, intensities, and regularity. Textural inpainting works best with heavily textured images. The texture contains a set of primitive texture pixels in repeated patterns which signify that a missing region can't be generated by using the structure information. To fill in a missing region using texture inpainting, it has to use information like spatial arrangement of color or intensities. For a large textured area first, perform image segmentation on the areas and then choose the corresponding textures from the image.

The combined structural and textural inpainting method simultaneously inpainted an image using their respective methods for filling the missing regions. The structure and texture both play an important role in the generation of the missing regions. In this method, the input image is divided into two images, one containing the image structure and other containing image texture. The output image is generated by combing the structure and texture inpainted images.

III. RELATED WORK

There are different image inpainting approaches are available and that are classified into the following way: (i) Partial Differential Equation (PDE) based inpainting (ii) Texture Synthesis based inpainting (iii) Exemplar based inpainting (iv) Hybrid inpainting. Partial Differential Equation (PDE) based algorithm for Image Inpainting is proposed by Bertalmio et al [1]. This algorithm is the iterative algorithm. The PDE based algorithms persist the geometric and photometric information that arrives at the border of the occluded area into the area itself. This is done by passing on the information in the direction of minimal change using the isophote lines. This algorithm will produce good results if missed regions are small ones. Texture synthesis based algorithms [2] are used to complete the missing regions using related neighborhoods of the damaged pixels. The texture synthesis algorithms generate the new image pixels from initial image pixels and also try to maintain the local structure of the image. The exemplar-based method has two important phases. The first phase is prioritizing the filling order. In these pixels on the continuation of image structure get a higher priority to ensure the correct structure propagation. The second phase is the selection of the best matching patch. After pixel was filled-in by this strategy, the priority term would be updated and re-ordered. The process is repeated until all the pixels in the missing region are filled-in. The hybrid inpainting technique is also known as image completion. This technique combines both texture synthesis and Partial Differential Equation based inpainting for filling the hole. The main idea behind this technique is that it decomposed the image into two separate parts that are Structure region and texture region. These separated regions are filled with edge propagating algorithms and texture synthesis techniques [3]. It is used for filling a large target (missing) regions. It also preserves both structure and texture effectively. It requires more computational time for filling large holes.

IV. ANALYSIS OF VARIOUS IMAGE INPAINTING ALGORITHMS

3.1 Context-Aware Semantic Inpainting Method [4]

In this paper, Semantic image inpainting has been done by using the framework of generative adversarial networks (GANs). They proposed a Context-aware semantic inpainting (CASI) method that consists of a Fully Convolutional Generative Network for better maintaining the original structures. It also has revised perceptual loss for capturing the semantics of the image context. Context-aware loss and perceptual loss function measure the similarity between a generated image and its ground-truth (real) image. This network takes an image as an input, where the hole is filled with the mean pixel value of available image information. The missing region is generated by point-wise multiplication with a mask. The output of the generative network is a synthesized image and both input and output have the same size. The generated output image is cropped and placed within the image context to form a composite image, via merging the known context region and the synthesized missing region. The discriminator network receives the newly generated image and the ground truth and tries to classify the received content as either "real" or "fake".

3.2 Diffusion-Based Inpainting in Digital Images [5]

In this paper, they use diffusion-based inpainting for digital image inpainting. The diffusion-based methods exploit smoothness priors and partial differential equation (PDE) to propagate the structures from the outside to the inside of the unknown region. A typical diffusion-based inpainting method was proposed by Bertalmio et al. [2] in 2000. In this work, the image Laplacian is used as a smoothness predictor for describing the local structural information, and an anisotropic model is employed to propagate the image Laplacian along the direction of the image isophote, which is perpendicular to the image gradient in each pixel point. Formally, the algorithm updates the pixel intensities iteratively inside the unknown region by solving the following equation:

$$I^{t+1}(x,y) = I^{t}(x,y) + t' \cdot dI^{t}(x,y), \forall(x,y) \in \Omega$$

Where t is the iteration time, t' is the update speed, and $dI^{t}(x,y)$ is the update signal for $I^{t}(x,y)$. $dI^{t}(x,y)$ is given by:

$$dI^{t}(x,y) = \nabla(\Delta I^{t}(x,y)) \cdot \nabla I^{t\,\perp}(x,y)$$

Where ∇ is the gradient operator, ΔI represents the image Laplacians, and $\nabla I^{\perp}$ is the isophote direction (perpendicular to the gradient direction). The term $\nabla(\Delta I) \cdot \nabla I^{\perp}$ represents the derivative of ΔI in the isophote direction. In the initial state, $t = 0$ and $I^{t} = I0$. After several iterations, a convergent status is obtained such that $dI^{t} = 0$, and the resulting inpainted image is defined as the output of the convergent status. After convergence, there is no variation in the image Laplacians ΔI in the directions of the isophote $\nabla I^{\perp}$, meaning that the image information (i.e., the Laplacians) is propagated inside the unknown region in a way that aims to preserve the isophote directions.

3.3 Image Inpainting Using Nonlocal Texture Matching and Nonlinear Filtering [6]

In this paper, they proposed an effective exemplar-based image inpainting method that uses a new Gaussian-weighted nonlocal texture similarity measure to find best matching exemplars for each target patch, which are then combined together using the alpha trimmed mean filter to fill in each pixel within the target patch. The given image inpainting algorithm generates fundamental textural details effectively. The given inpainting algorithm is an iterative process, in each step first apply a priority function that is a combination of a confidence term and a data term to choose the next target patch. The confidence term is the ratio of known pixels within the patch and data term. The data term is the dot product of the isophote vector and normal vector. The target patch has a known portion from the source region and an un-known portion from the missing region. Then select the target patch. Then for choosing the best matching patches from the source region patches, a new nonlocal texture similarity measure is used. After that apply the α-trimmed mean filter to the best-matched patch to generate each missing pixel. Then fill the missing region of the target patch by copying the corresponding part of the candidate patch. It also smoothens the pixel intensity to generate inpainted images like a ground-truth image.

3.4 Sparsity-Based Image Inpainting [7]

In this paper, they use sparsity-based inpainting for digital image inpainting. The sparsity-based inpainting use more general prior knowledge for filling the missing regions. The image inpainting problem can also be handled assuming sparsity priors. There are the following steps in the sparsity-based image inpainting process: (i) Vectorized the block of an image, assuming that vector can be represented by a predefined redundant dictionary and a sparse vector (ii) Use the sparse vector and another part of the predefined dictionary to learn the inpainting signals. In sparsity-based inpainting, it is assumed that both known and missing regions have the same sparsity in signals. Therefore, they have the same sparse vector in the sparse learning process. Compared with other types of image inpainting operations, e.g.

diffusion-based inpainting and exemplar-based inpainting the sparsity-based inpainting use more general prior knowledge in image processing.

3.5 Perceptual Adversarial Networks for Image-to-Image Transformation [8]

The given Perceptual Adversarial Networks (PAN) for image inpainting gives a basic framework of learning to map from input images to the desired output image. Inspired by GANs, PAN is composed of an image transformation network T to generate the transformed images and a discriminative network D to calculate the difference between the newly generated images and the ground-truth images. The PAN uses both the perceptual adversarial loss and the generative adversarial loss as a new training loss function known as PAN loss. The perceptual losses explore the difference between high-dimensional representations of images extracted from a well-trained classifier. Minimize the perceptual adversarial loss with respect to image transformation network T to generate an image like ground-truth. The new PAN loss gives better performance on quantitative measurements.

3.6 Edge-aware context encoder for image inpainting [9]

The given framework consists of two parts, an edge map generation part and a context encoder based inpainting part. In this method, edges are extraction from a masked image and then completion of edges in the missing region using a full-convolutional network. The entire edge map combined with the known region is given as the inputs to the modified context encoder network to predict the missing region. The Edge-aware Context Encoder method recovers the texture according to edge structures. In order to provide boundary and main structures for the texture inpainting, it prefers to extract the edges of objects rather than fine texture details. Therefore, it adopts a CNN based Holistically-Nested Edge Detection (HED) model. It deals with the holistic image in the process, enabling the extraction of high-level boundary information. After recovering the connectivity between edges the inpainting network is trained by regressing the ground truth content of the missing region. Reconstruction loss and adversarial loss are used together to handle the similarity of the generated missing region. Rather than taking GAN loss, it uses the Wasserstein GAN (WGAN) loss due to its ease of training and good results.

V. CONCLUSION

This paper presents a brief overview of different techniques and algorithms for Image Inpainting. We discuss several algorithms in the aspects of texture and structure, from that we can say that both structure and texture play an important role in image inpainting. All the given algorithms have their own benefits and drawbacks. Isotropic diffusion-based algorithm [5] is suitable only for packing the regions which are small. When missing regions are large then Partial Differential Equation (PDE) [1] based algorithm takes a long time and does not produce good results. Texture Synthesis Based Inpainting Performs well in approximating textures. It produces good results if the missed region is a small one. It takes a long time if the target region is large. Some blurring effect is presented in the output image. It is Difficult to handling natural images in Texture Synthesis Based Inpainting algorithms. Textural based inpainting approaches mainly use patch based technique to fill the missing region in the image. The structural based inpainting methods are complex but give good results. To preserve both structure and texture combined structure and texture image inpainting techniques can be used. Hybrid inpainting Handle large holes effectively and preserves both structure and texture. GAN also gives good results for image inpainting but it takes too much time for training large datasets. All these image inpainting techniques can be used on video also.

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