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# Exploration of Image Inpainting approaches and challenges: A Survey

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**Abstract:-** The process of restoring missing areas of an image is referred to as "image inpainting." It is a significant challenge in the field of computer vision and a crucial feature that is utilized in a wide variety of image and graphics programs. Although image inpainting, also known as the art of repairing old and worn images, has been around for a couple of years, it has recently gained even more popularity due to recent developments in image processing techniques. Image inpainting can be thought of as the art of restoring old and worn images. Automatic image inpainting has become an important and challenging area of research in image processing due to the advancement of tools for image processing and the flexibility of digital image editing. Automatic image inpainting has found important applications in computer vision and is also becoming an important image processing application. Due to its high significance and effectiveness in a variety of image processing applications such as, for example, object removal, image restoration, manipulation, re-targeting, compositing, and image-based rendering, researchers have studied the image inpainting problem intensively over several decades. The process of eliminating or filling in a missing area in an image is referred to as "image inpainting," It is defined as in-depth knowledge of the image details in terms of its structure and texture. It is considered to be one of the most challenging subjects in image processing. This article presents a survey of most image inpainting techniques and summarizes them, along with comparisons that include the benefits and drawbacks of each method. These comparisons and summaries can assist researchers in evaluating their own proposed techniques against existing ones.

**Keywords:** Image inpainting, Texture synthesis methods, Exemplar-based texture synthesis, Generative Adversarial Network, Convolutional Neural Network.

## 1. Introduction

The image inpainting operation is the practical use of the computer to fill and repair broken areas of source image in order to finally achieve visualization rationality. Moreover, an image inpainting algorithm is a kind of image processing method that repairs missing information in an original image, or removes specific information in an image by using undamaged information from the original image while ensuring that the quality of image and its natural effects are not damaged. The purpose of image inpainting procedure isn't to restore on the basis of original image source, but rather to fix and reconstruct the images that are approximate to original image source [1]. The image inpainting procedure, as a common image editing procedure, aims to fill the missing or masked areas in original images with reasonable, plausible and synthesized contents. Image inpainting algorithms have been widely used in several research fields, including computer science and technology, electronic systems, machine learning, and computer vision. Traditional image inpainting algorithms have undergone nearly two decades of development. From the initial repairing algorithms utilizing a partial differential formula to image repairing algorithms based on image samples, existing information is mined and utilized from the image to repair the changes to a given area. The main objective of image inpainting is to produce completed recovered images in an unnoticeable manner to the human visual system. Image inpainting has various applications, such as image restoration, image editing, removal of the unwanted object image denoising, etc. furthermore the digital Image In-painting has various applications such as restoration of damaged old printing and old photographs, error recovery of images and videos, multimedia editing (computer assisted), transmission loss and replacing large regions in an image or video for privacy protection. The concept of image inpainting existed very long year's back and from the birth of computer vision, researchers are looking for a way to carry out this process automatically. Image Inpainting restructure the damaged region or mislaid parts in an image utilizing spatial information of neighboring region. Furthermore. Some different applications of image inpainting are shown in Fig. 1.

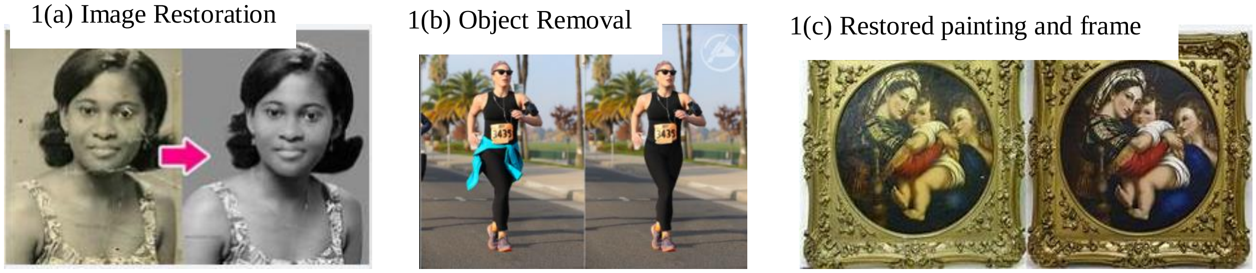


Figure 1. Different application of Image inpainting

Some of the inpainting approaches displayed in figure 2 have been great successes in nearest neighbor searching, which is the process of synthesizing images using patches or pixels. However, one of the difficulties associated with inpainting is preserving a realistic structure and texture in the final image. Traditional approaches, for instance, may try to fill in missing pixels by employing image patches taken from already existing regions. Alternatively, they will employ the diffusion process to transmit pixels into a hole region from regions with high pixel similarity. Although these algorithms can produce vibrant textures for background inpainting, they frequently fail to capture high-level semantics, which results in images that are not realistic and contain repeated patterns. Furthermore, these procedures do not produce plausible results. These traditional methods were suitable for completing small missing regions such as a crack in an image. However, with the evolution of digital images, the task of inpainting became more complex as larger regions now are required to be filled regardless of its size or location across the image. Unfortunately, image inpainting traditional methods could not handle filling larger complex regions.

Removing objects from images using image inpainting can reach improved performance in the future, but when the image editors hide traces using sophisticated techniques, the detection of forgery and the inpainting of image become difficult. For that reason, almost all detection approaches attempt to handle this by detecting the abnormalities of similarity between blocks of the image that can be affected during the postprocessing operation. This work summarizes different methods for image inpainting using different techniques including sequential-based, CNN-based or GAN-based methods.

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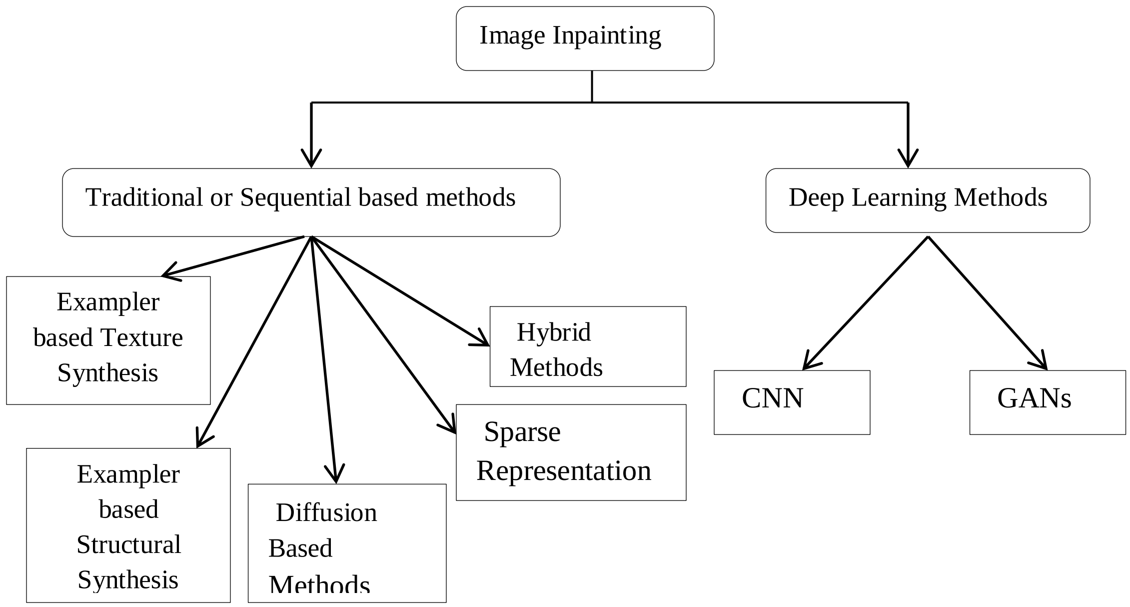


Figure 2 shows a hierarchical representation of the various categories of inpainting in their respective groups

The paper's main contribution is exploring the various types of traditional and deep learning-based image inpainting techniques and their effects. Research difficulties and suggestions could also be mentioned.

The remaining paper is organized as follows: Section 2 explains the traditional image inpainting techniques, Section 3 describes the deep learning-based algorithms, Section 4 highlights the research problems and ideas, and Section 5 concludes the survey.

## 2. Traditional Image Inpainting Algorithms

The majority of well-known traditional image inpainting methods that do not involve deep learning methodologies are discussed in this section. These algorithms can be broken down even further into the five sub-categories shown in Figure 2.

### 2.1 Diffusion-Based Inpainting:

For physical phenomena like heat transfer in physical structures, diffusion is derived from spreading local information with smoothness constraints. PDEs can formalize these processes, and PDE-based regularization is utilized to perform diffusion. By seamlessly propagating local image structures from the hole's exterior to its interior, diffusion-based inpainting "imitates" competent painting restorers' actions. In 2000, Bertalmio et al. [2] were the first to use regularization or diffusion for image inpainting. Diffusion-based inpainting is the process of filling an area by diffusing information from a known area into the target area . Diffusion algorithms are built on vibrational mathematics and partial differential equation (PDE) methods. The diffusion-based inpainting algorithm produces precise results when filling in non-textured or misplaced areas. Figure 3 depicts how the PDE approach propagates (or diffuses) neighboring data into the center of the hole. The illustration also shows the regions of well-known (source) and unknown (hole). Massive textured areas are filled with a fuzzy appearance due to the diffusion process. As a result, any PDE-based method can be applied to fill in a small, non-textured target region. There are several types of diffusion, including linear, nonlinear, isotropic (diffusion is the same in all directions), and anisotropic (diffusion changes depending on the object's orientation).

Figure 3. Illustration of Diffusion-Based Inpainting:

### 2.2 Exampler based Texture Synthesis

Many definitions and typologies of textures have been offered during the past four decades in digital image processing. An early method of image inpainting was based on algorithms that synthesize textures. Using patching techniques, the broken pixel is replaced with one from a nearby area that is similar to fill in the gap left by the damaged one. Figure 4 shows how texture generation adds additional pixels from an input taken from a known location and preserves the image structure. Most inpainting techniques use this technique, which involves copying and duplicating patches from existing image data to fill in the blanks where a matching patch does not exist. However, nature would be complete if the missing section were filled in with a similar visual look. Texture synthesis is more effective [3–4].

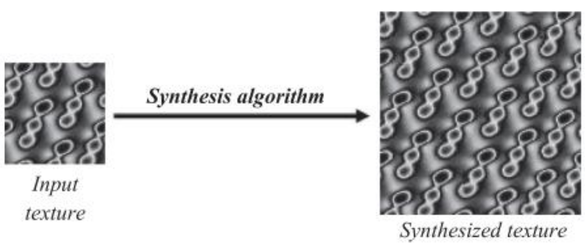


Figure 4. Illustration of Exampler based Texture Synthesis

#### 2.2.1 Typology of texture synthesis methods

Over the last few decades, research in texture synthesis has resulted in the creation of a wide range of synthesis methods. These methodologies can be divided into three broad groups: procedural, exemplar-based, and model-based texture creation strategies.

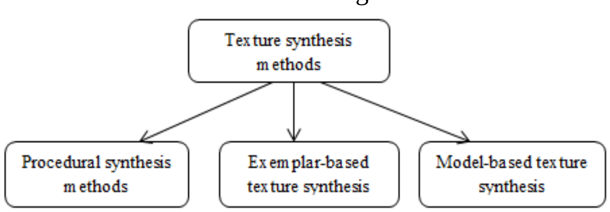


Figure 5. Classification of Texture Synthesis Methods

***Procedural synthesis methods :*** Methods of procedural texture synthesis involve the creation of textures through the application of mathematical functions or algorithms that can be carried out with a predetermined amount of computational expense. As a result, procedural methods are tools that are ideally suited to producing the textures of objects in virtual environments, such as video games.

***Exemplar-based texture synthesis:*** In order to function, these methods require the input of one or more example textures. The majority of them generate textures by directly copying the pixels or patches (sub-images) from the images fed into the program. Therefore, the purpose of these methods is to produce a new texture designed to be as comparable to the model (input) texture or exemplar as is humanly possible.

***Model-based texture synthesis:*** These techniques involve building a probabilistic model capable of being used in describing the texture and synthesizing it. The model's parameters ought to capture the important observable qualities of the texture.

### 2.3 Exemplar-Based Inpainting

Texture synthesis techniques eventually led to the development of inpainting based on examples. It's difficult to fill in large textures with diffusion approaches. However, the example makes filling in large target regions easier by utilizing two distinct processes: 1) picking the best matching patch and 2) performing priority assignments. Filling orders are based on priority and are determined by the exemplar, which aids in selecting the best matching patch from source regions (i.e., the regions closest to the target region). It is possible to discriminate between structure and texture by determining the pixel with the highest priority for each patch that has been briefly illustrated in [5], [6], and [7]. The missing part is then pixelwise reconstructed with the linear combination of these patches. Finding the best candidate is critical because it ensures a good match between the source and target regions. Finding the best candidate According to the filling order, a pixel from the closest neighboring patch is copied and filled into the target region. It seeks out the most comparable patch and duplicates the pixel from that nearby patch. The following are the steps for example-based inpainting: The exemplar-based image inpainting algorithm is a patch-based approach that restores target regions in the input image by using these steps.

1. Extract the target regions from the provided input image.
2. Produce a binary mask with dimensions identical to the input images. The portions of the target image to be inpainted must correspond to the nonzero pixels in the mask image.
3. Identify the region that is the source. The source region consists of all of the regions in the input image, except for the regions intended to be the targets. In other words, the source region equals the input picture minus the target regions.
4. Using either the gradient or the tensor technique, determine the patch priority for each patch, each of which has dimensions of p by s and is centered on a boundary pixel in the target region.
5. Identify the repair that has the highest priority. This particular patch will serve as the target for the subsequent inpainting.
6. Using the sum of square differences, search the source region for the patch closest to the target patch you have (SSD).
7. Transfer the image data from the patch that closely matches the destination patch.
8. Ensure that the input image, mask, and patch priority value are all updated.
9. Continue to repeat steps 4–8 until the desired areas have been inpainted.

Figure 6(a) Extract the target regions

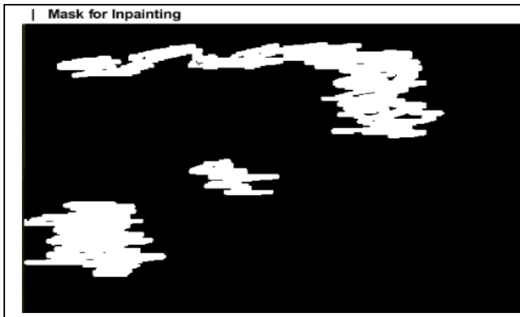


Figure 6(b) Binary Mask

Figure 6(c) Inpainted Image

Figure 6. Illustration of Exemplar-Based Inpainting

**2.4 Hierarchical Super-Resolution Based Inpainting**

This adds exemplar-based inpainting that combines inpainting and super-resolution. This method converts a high-resolution image to a low-resolution image, then inpaints it. This simplifies both the computational and visual aspects of working with image structures. First, pick the editing area in Hierarchical Super-resolution. A selected area within the limit will be colored. Convert high-resolution images to low-resolution. The low-resolution input image is broken into small patches and inpainted one by one. The resulting image is turned into a high-resolution image through a single-image super-resolution technique.

This methodology was introduced by Olivier Le Meur et al. [8] for exemplar-based inpainting. This method is extensively used, although it has many drawbacks, the most prominent of which is a lack of control over patch size and order. First, an input image is inpainted using an exemplar before applying hierarchical super-resolution. In this case, the low resolution is incorporated multiple times. The results are quickly integrated and turned into a single image by utilizing the super-resolution process via loopy belief propagation. Using this method, high-resolution details can be reconstructed quickly and accurately. The primary method used is extracting high-resolution patches from an image's recognized regions. It is easier to paint low-resolution images than high-resolution ones. The method's core principle is that it is based on the idea of

1) The original image is re-sampled at a lower resolution to produce the final image.

2) A low-resolution image has defects, so an inpainting algorithm is used to fix it. This algorithm employs dictionary construction and similarity computing to fill in the holes.

3) The quality of the image is increased by developing a higher resolution from the image that was inpainted to recover details from the areas that were removed.

Figure 7(a) Mask

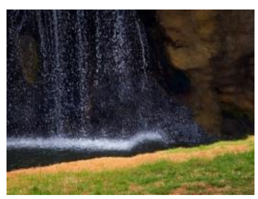

Figure 7(b) Super-resolution-based inpainting.

## 2.5 Hybrid Methods

It is a method of image modification where missing parts of an image are estimated and replaced with available or external data. It combines the advantages of both diffusion-based and enhanced exemplar inpainting methods. The image's structure is treated with a diffusion-based approach, followed by adaptive patch size–based inpainting that makes the Hybrid Method. One of the hybrid inpainting methods was developed by Bertalmio et al. [10], who created an algorithm based on the concept of decomposing the original image into two layers. This method is considered to be one of the hybrid inpainting methods. The textural qualities should go in the second layer, whereas the structural characteristics should go in the first layer. The first image would be processed by an algorithm for structural inpainting [8], while an algorithm would handle the second image for texture synthesis proposed by Efros and Leung [9]. Both of these algorithms would be applied to the respective images. Both of these processes leave their mark on the finished product somehow. Atzori and de Natale [12] came up with a suggestion for an additional hybrid technique. In this particular instance, the process of restoration begins with matching the contours that intersect the edge of the occluded area that is located inside the object. This process will result in smaller sections, which will be filled by copying blocks from the data perimeter. Rareş et al. [11] recommended that while combining the edge contours that overlap the damaged region, both the local and global information should be considered. This was one of their recommendations. In this way, pairs of more precise lines will be obtained, but matching them will become more complex. The values of the restored pixels are then assigned based on the pixels located close to the newly obtained contours and the pixels located along the edges of the occluded area.

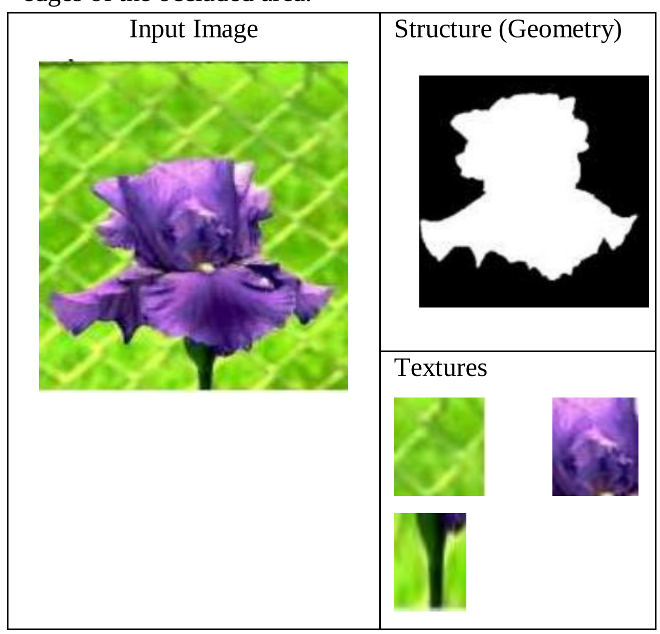


Figure 8(a) Illustrations of Hybrid methods

 

**Table 1. Traditional Image Inpainting Techniques Overview**

| Techniques | Inference | Future Work |
|---|---|---|
| Diffusion-based image in painting | • It generates good results when filling in small or gap regions.<br>• Blur effect, which becomes obvious when filling larger regions<br>• Preserves edge information.<br>• Suitable for completing lines and curves.<br>• Does not produce verbatim copies in the synthesized textured region.<br>• Maintains the structure of the inpainted region. | • To extend this approach for filling in large holes<br>• Fails to inpaint large textured regions, resulting in blurry artifacts on image. |
| Texture synthesis and Exemplar-based image inpainting | Similar patch doesn't exist while synthe sizing regions and not designed to handle curved structures | Extensions include accurate Propagation of curved structures in still photograph and use of inpainting in videos. |
| Exemplar based image in painting | By utilizing image information from multi ple samples helps in improving visual qual ity | Alternate weighing functions and methods and can be used for selecting samples. |
| Hierarchical Super Reso lution | Experimental results on a wide variety of images have demonstrated the effectiveness of this method | More images can be used for building dictionary to be used in super resolution |
| Sparse representation Methods | • Inpaints facial images with high exposure to light.<br>• Allows change in light intensity. | • May not work well on natural scene images.<br>• On image reconstruction, the damages pixels.<br>• Must be in the vertical direction. |
| Hybrid | • Preserves edge and restores smoothness. Impressive results on the linear structure of the image improve the speed.<br>• Smoothness is restored and structure and texture are preserved of image. | • If the damaged area is large and inappropriate, blocky image is obtained<br>• Computational complexity with no guarantee in convergence. |

## 3. Deep Learning Methods

Recent work [13] summarized the image inpainting technology based on deep learning. Omar Elharrouss et al. [13] divided the image inpainting model methods proposed in some classic papers into three categories from a global perspective, namely, sequence-based methods, CNN-based methods and GAN-based methods. Qiang et al. [14] summarized the main image inpainting methods based on deep learning in recent years and classified the existing methods into three network structure types of image inpainting methods based on convolutional autoencoder network, generative adversarial network and recurrent neural network according to the inpainting network structure.

Image inpainting [14] is a research field of image processing. It aims to fill the missing or masked regions of the image with generated content and make the repaired image visually realistic. Image inpainting technology has been widely applicated in many fields, including ancient book restoration, medical image processing, and PhotoShop processing. Therefore, the research of image inpainting is worth studying. Due to the complexity of the natural images, there will be obvious fuzzy phenomena in the region of the repaired image and the boundary between the original region and the repaired region, which is a main difficult issue in the work of image inpainting. Also, how to ensure the semantic correctness of the repaired region is one of the difficulties in the task of image inpainting. In order to address these problems of image inpainting, existing methods categorize into two types: one category is texture synthesis methods based on the patch, the main idea is to find the boundary of the missing region to fill in the missing part of the image.

### 3.1 CNN based Technique:

CNN has proved powerful in many tasks, including single image inpainting [20], the main idea is to extract the features of the image through the deep convolution neural network to understand the image, and then to fill the missing region. Deep neural networks have been successfully applied to problems such as image segmentation, image super-resolution, coloration and image inpainting. Several methods have been proposed for image inpainting using convolutional neural networks (CNNs) or encoder-decoder network based on CNN.A typical patch-based method is a Patch-Match method proposed by Barnes et al. [15], which searches for the matching patch from the rest part of the image to fill in the missing region, resulting in more reasonable texture information. This method has an excellent effect on background inpainting. However, it does not perform well in the face of complex images (face, natural images) inpainting, and the result of inpainting will be very vague. Similarly, other patch-based methods [17] [18] and exemplar-based methods [16] [21] are weak in inpainting the missing regions with complex structures. The reason is that the texture synthesis method based on the patch is still not enough to obtain the high-level characteristics of the image. With the rapid development of deep learning, the appearance of the feature learning-based image inpainting method exactly fills the defect of the traditional image inpainting methods, which is lack of high-level coherence and difficult to deal with the problem of large areas or complex structures missing. Neural networks are more powerful to learn high-level semantic information of images and CNNs are effective tools for image processing [20]. Neural networks do more and more image inpainting tasks. Pathak et al. [30] proposed the model Context Encoder, which combines encoder-decoder and Generative Adversarial Network(GAN) [19] to train in an unsupervised method. They use the adversarial loss to make the repaired image as real as possible and generated realistic results. But context encoder has drawbacks: the fully connected layer cannot save accurate spatial information and context encoder sometimes creates blurry textures inconsistent with surrounding areas of the image.

### 3.2 Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) are a powerful class of neural networks that are used for unsupervised learning. It was developed and introduced by Ian J. Goodfellow in 2014.

In GANs, there is a generator and a discriminator. The Generator generates fake samples of data(be it an image, audio, etc.) and tries to fool the Discriminator. The Discriminator, on the other hand, tries to distinguish between the real and fake samples. The Generator and the Discriminator are both Neural Networks and they both run in competition with each other in the training phase. The steps are repeated several times and in this, the Generator and Discriminator get

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better and better in their respective jobs after each repetition. The working can be visualized by the diagram given below as shown in figure 9:

Here, the generative model captures the distribution of data and is trained in such a manner that it tries to maximize the probability of the Discriminator in making a mistake. The Discriminator, on the other hand, is based on a model that estimates the probability that the sample that it got is received from the training data and not from the Generator.

The GANs are formulated as a minimax game, where the Discriminator is trying to minimize its reward V(D, G) and the Generator is trying to minimize the Discriminator's reward or in other words, maximize its loss. It can be mathematically described by the formula below:

$$\min_G \max_D V(D,G)$$

$$V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G($$

Where G = Generator

D = Discriminator

Pdata(x) = distribution of real data

P(z) = distribution of generator

x = sample from Pdata(x)

z = sample from P(z)

D(x) = Discriminator network

G(z) = Generator network

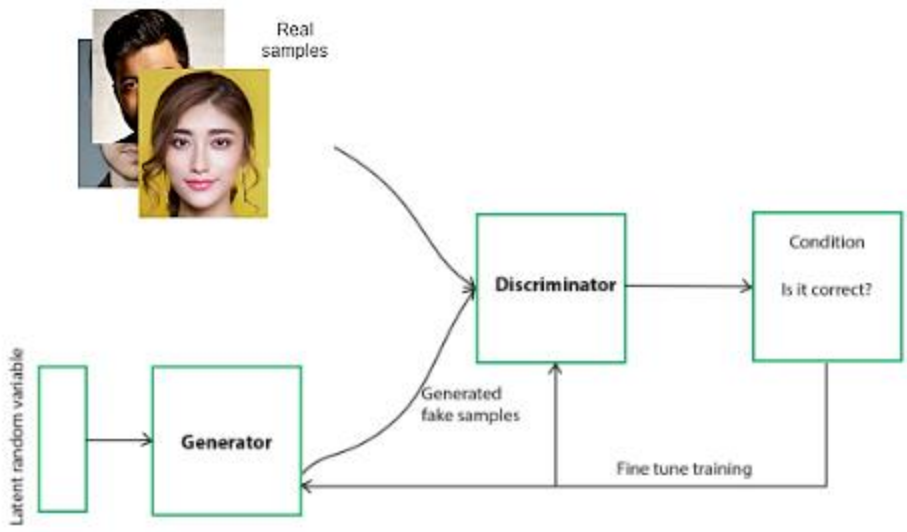


Figure 9. Flow model of Generative Adversarial Network

**Generator**

Inpainting is part of a large set of image generation problems. To solve this problem, we use an auto-encoder as the generator of our model. The auto-encoder contains two networks: an encoder and a decoder. In this paper, we input the image to be repaired into the encoder and encode it into code, and then reconstruct and generate the repaired image via decoder decoding.

**Discriminator**

The generator is responsible for inpainting the missing or masked regions of the image. However, the Generator cannot guarantee that the generated regions are accurate or consistent with the original image. In order to ensure that the generated image is much more realistic, this paper uses the discriminator as a binary classifier to distinguish whether the image comes from real data distribution or generated by the generator. Also, the discriminator helps to improve the generator's ability to generate more realistic images to fool the discriminator. Deep learning-based image inpainting approaches that can generate the missing pixels in an image with good global consistency and local fine textures.

**Table 2. Deep learning-based inpainting approaches**

| Approach | Significance | Advantages | Disadvantages |
|---|---|---|---|
| Context Encoder (CE)[22] | first Generative Adversarial Networks (GANs) [23] based inpainting algorithm | • Doesn't require high memory usage<br>•Simple<br>•Performs well for center square missing regions | • Fails if the location of the missing region changed<br><br>• Does not support random missing regions |
| Multi-Scale Neural Patch Synthesis (MSNPS, 2016) [24] | Enhanced version of CE | Performs well for center missing region | Slow algorithm<br>Does not support random missing regions<br><br>Fails when the image is not center symmetric images |
| Globally and Locally Consistent Image Completion (GLCIC, 2017) [25] | It is a milestone in deep image inpainting as it defines the Fully Convolution Network with Dilated Convolutions for deep image inpainting | • Performs well<br>• Efficient | Does not support random missing regions<br>• Unable to handle complex structures |
| Patch-based Image Inpainting with GANs [26] | two advanced concepts namely residual learning [27] and PatchGAN [28] were embedded in GLCIC to further boost its inpainting performance. | • Efficient<br>• Performs well for center square missing regions | • Added artifacts<br>• Fails in the case of images with different textures and colors |
| Shift-Net [29] | takes both the advantages of modern data-driven CNNs and the conventional "Copy-and-Paste" method in the form of Deep Feature Rearrangement by using the proposed shift-connection layer. | Shift-Net inherits the advantages of exemplar-based and CNN-based methods, | Guidance loss that encourages the decoded features of the missing parts (given a masked image) to be close to the encoded features of the missing parts (given a good-conditioned image).<br><br>Shift-connected layer with shift operation allows the network to effectively borrow the information given by the nearest neighbours outside the missing parts to refine both the global semantic structure and local texture details of the generated parts. |

 

| | | | |
|---|---|---|---|
| Generative Image Inpainting with Contextual Attention (CA, 2018)[30] | Can be regarded as an enhanced version or a variant of Shift-Net [31]. | • Performs well for fixed square missing region •Supports highresolution images | • Does not support random shaped missing region |
| Generative Multi-column Convolutional Neural Networks (GMCNN, 2018) [32] | The multi-column structure method | It can decompose images into components with different receptive fields and feature resolutions. | Expands the importance of sufficient receptive fields for image inpainting and proposes new loss functions to further enhance local texture details of the generated content. |
| DeepFill v2 (A Practical Generative Image Inpainting Approach, 2019) | This can be regarded as an enhanced version of DeepFill v1 [9], Partial Convolution [33], and EdgeConnect [34]. | achieves high-quality free-form inpainting than previous state-of-the-art methods | Gated Convolution which is a learnable version of the Partial Convolution. By adding an extra standard convolutional layer followed by a sigmoid function, the validness of each pixel/feature location can be learned and hence optional user sketch input is also allowed. |
| A Novel Face Inpainting Approach Based on Guided Deep Learning | A new novel approach for face inpainting is proposed which can capture and preserve the identity of each human face in images while reproducing the missing irregular region in images | • Efficient • Preserve human identity in images • Works with random shaped missing regions | • Fails to produce good results if the human face is not centered in images • Does not support highresolution images |

## 4. Image Inpainting Challenges

After detailed investigation on Image inpainting with several traditional and deep learning methodologies we noticed some of the research challenges.

Challenge 1: Research is required on 2D image inpainting and depth map inpainting

Challenge2: working with structural, textural or both the methods simultaneously for image inpainting .

Challenge 3: There are no current methods that can reliably inpaint large holes in depth map.

Challenge 4 : Depth inpainting is still a challenging issue for medical image application .

## 5. Conclusion

Computer vision applications rely on image inpainting to perform various data modifications, including image quality enhancement, restoration, etc. A brief survey of image inpainting is provided in this paper. Traditional and deep learning algorithms are among the options that have been discussed. Different approaches to traditional and deep learning were discussed here. None of the methods studied can correct for every sort of distortion in an image. However, the results obtained by utilizing deep learning are pretty encouraging for each category examined. On the other hand, deep learning has difficulty with its high computational complexity and memory requirements. Researchers must focus more on developing algorithms that can deal with both simple and complicated structures in the future. Computer vision applications rely heavily on image inpainting because of the vast amounts of data that can be altered utilizing image editing tools. These applications include wireless image coding and transmission, image quality improvement, image restoration, etc. An introductory survey of image inpainting is offered in this paper, i.e., sequential (non-learning) techniques, CNN-based approaches, and GAN-based approaches are just a few of the ways discussed. In addition, we noticed a few research challenges in attempting to compile various methods for dealing with various potential future suggestions.

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