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# Image Inpainting: An Overview

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**Abstract –** Over the years' Researchers have intensively studied the image inpainting problem due to its great importance and effectiveness in various image processing applications such as human and object security, object removal, face processing applications. The process of adding or erasing missing areas from images is known as image inpainting. Although it necessitates a profound comprehension of the image details in terms of texture and structure, it is regarded as one of the most difficult topics in the field of image processing. The majority of image inpainting techniques, various tools exploited in each of the reviewed works, challenges and limitations with image inpainting techniques as well as the datasets used are reviewed in this paper which may be useful for researchers in assessing their own proposed methods.

**Index Terms –** Image inpainting, Inpainting techniques, Tools, Datasets

## I. Introduction

The concept of image inpainting can be traced back to a traditional method employed by artists in the past to mend deteriorated paintings or photographs. It involved addressing minor imperfections such as scratches, cracks, dust, and spots in order to preserve the quality as closely as possible to the original piece. To illustrate this manual process, refer to Figure 1 which showcases inpainting performed by hand. The advancement of computers during the 20th century, their widespread daily usage, and the development of digital tools capable of manipulating images have prompted users to value the art of image editing, such as restoration, as well as the utilization of on-screen visual display and special effects for images. Consequently, image inpainting, a cutting-edge restoration technique, has emerged. Within the context of computer vision and graphics, inpainting refers to a method that employs neighboring pixels to reconstruct damaged or flawed segments of an image. The goal is to achieve a restoration that is visually indistinguishable from the rest of the image. These damaged areas consist of



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isolated pixels enclosed by a cluster of known neighboring pixels. When reconstructing these disconnected pixels, the inpainting method relies on known information to fill in the gaps of unknown regions [2].

**Fig.1.** Hand inpainting was executed by an artist (courtesy of Thottam, 2015).

Image inpainting, a field within image processing, involves the completion of missing sections in images based on predicted estimations using surrounding pixel information [34]. The primary objective is to seamlessly generate recovered images that are imperceptible to the human visual system. Image inpainting finds application in various areas such as image restoration [35], image editing [36], removal of unwanted objects [37], image denoising, and more. It is crucial that the reconstructed image retains and respects the edge information present in the original image. Several techniques have leveraged the similarity in statistical parameters and geometric structures between known and unknown image pixels, leading to superior visual results [38] [36]. Image inpainting can be divided into two main categories: Traditional techniques and deep learning techniques. Traditional methods utilized either diffusion-based approaches, which generated local structures in the missing parts, or exemplar-based approaches, which filled one pixel/patch at a time while maintaining consistency with the surrounding pixels.

These traditional methods were effective for completing small missing regions like a split in an image. However, as digital images evolved, the task of inpainting became more challenging. Now, larger regions need to be filled, regardless of their size or location within the image. Unfortunately, traditional image inpainting methods were unable to handle the filling of larger and more complex regions [39]. This limitation motivated researchers to explore and identify alternative methods to address this problem. Deep learning has become a popular approach in addressing the intricate challenge of image inpainting due to its impressive track record demonstrated in previous years [32]. Image inpainting requires a thorough understanding of the structure, texture, and color data of an image in order to generate realistic visual results [1].

The potential uses of image inpainting are vast, and here we present the most prevalent and useful applications.

- ***Object Removal:*** With the aid of inpainting techniques, unwanted objects in an image can be effortlessly eliminated. This approach is particularly helpful when dealing with image tampering scenarios. An illustrative instance of this can be observed in Fig. 2, where the cage present in the original image has been successfully removed in the inpainted image [3] [7].
- ***Restoring Photos:*** Inpainting can effectively address the degradation of photos over time. It can also eliminate scratches caused by mishandling. Similarly, this technique proves valuable for

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restoring images from cultural archives and other sources. An illustration in Fig. 3 exemplifies the successful removal of scratches from an old photograph using inpainting [4] [7].

- ***Photo Retouching:*** Photo retouching is a popular application of image inpainting in the media industry. It involves manipulating photos of actors, actresses, models, and similar individuals by eliminating wrinkles, mole marks, or undesirable facial features to enhance their attractiveness. An example, shown in Fig. 4, showcases image inpainting used to remove marks, thereby making the face appear more appealing[5] [7].
- ***Text Removal:*** Image inpainting can serve the purpose of eliminating undesired elements such as text, stamps, copyright logos, and so on, from digital images. An instance of this application can be observed in Fig. 5 where a street image exhibits overlaid text, which is subsequently removed in the inpainted image [7].

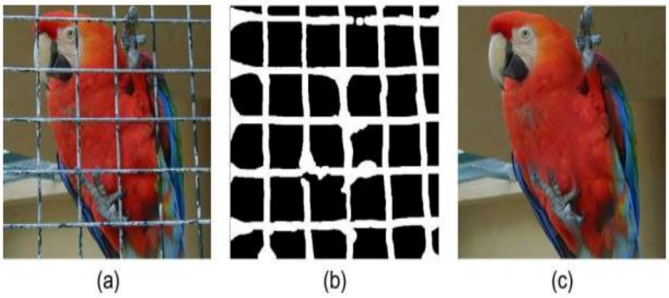


**Fig.2.** An example of image inpainting for object removal (a) original image, (b) binary mask ,and (c) inpainted image [3][7].

**Fig.3.** An example of image inpainting used in restoration, original image (left), restored image (right) [4] [7].


**Fig.4.** An example of image inpainting for photo retouching, original image (left), retouched image (right) [5] [7].


**Fig.5.** An example of image inpainting for text removal, original image (left), text removed image (right) [6].

## II. Image Inpainting Techniques

The emergence of the Internet era has ushered in a fascinating virtual realm of multimedia, where digital images play a vital role by carrying an immense amount of information. As a consequence, numerous scholars from academia and corporations have been captivated by the study of digital images. The demand for restoring old and damaged photographs, as well as adding color to black-and-white photos, has spurred research in the field of image inpainting. Currently, image inpainting technology has evolved, encompassing Non-Learning Methods and Learning Methods depicted in Figure 6 [8].

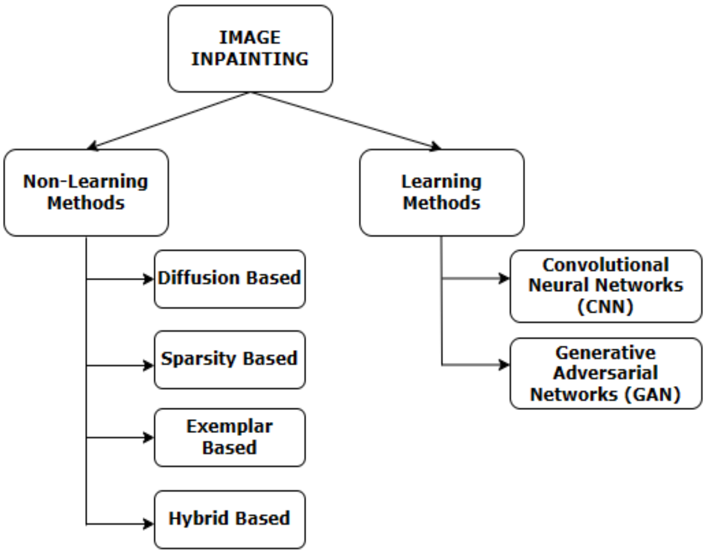


**Fig.6** Hierarchical design of Image Inpainting techniques

### Non-Learning Methods

In this section, we will cover a majority of renowned conventional image inpainting algorithms that refrain from leveraging deep learning techniques. These algorithms shall be further divided into the following four sub-categories:

- Diffusion Based Inpainting
- Sparsity Based Inpainting

- Exemplar Based Inpainting
- Hybrid Inpainting

**Diffusion Based Inpainting**

The concept of diffusion is derived from the notion of spreading localized information while adhering to smoothness restrictions, drawing an analogy to physical phenomena such as heat propagation in physical structures. These phenomena can be mathematically formalized using Partial Differential Equations (PDEs), and the process of diffusion is consequently executed through PDE-based regularization. In the context of image inpainting, diffusion serves to seamlessly extend local image structures from the surrounding area to complete the missing regions, resembling the technique employed by skilled painting restorators. The data under consideration is assumed to adhere to smoothness constraints and is progressively regularized through iterative steps, generating a continuous sequence of refined images. The process of image regularization can be localized by diffusing pixel values using PDEs, or alternatively, it can be formulated as the minimization of a functional that quantifies global variations within the image. Furthermore, in order to preserve the integrity of edges, the regularization (or smoothing) must align with the directions provided by the local image structure. If the pixel is situated along the contour of an image, smoothing should be carried out in the direction of the contour rather than crossing boundaries. However, if the pixel is positioned within a homogeneous region, smoothing can be performed in any direction. Initially, it is essential to extract the local image geometry and then employ PDEs or variational methods to depict continuous evolutions of the image and its structures [9]. An example, shown in Fig. 7, showcases diffusion based image inpainting.


**Fig.7.** An example of Diffusion based image inpainting (a) original image, (b) inpainted image [10].

**Sparsity Based Inpainting**

Sparse representation inpainting methods operate under the assumption that images consist of natural signals that can be decomposed into sparse components over a redundant dictionary. This redundant dictionary serves as a compressed or encoded version of the original image vector. Although both the original image and its sparse representation have the same number of elements, the latter mostly comprises zero entries, effectively reducing noise and emphasizing the essential information within the image. The objective of inpainting is to restore the missing regions in an image, assuming that these regions have a similar sparse representation to the existing regions. In 2007, Mairal et al. [13] proposed a dictionary learning algorithm tailored specifically for sparse decomposition of colored images with missing information, with a primary focus on image denoising. In 2009, Shen et al. [14] introduced an enhanced algorithm that offered a patch-wise sparse representation technique designed specifically for image inpainting. This method enabled users to define their own masks and ensured the preservation of both texture and noise consistency in the resulting inpainted images. Several inpainting results generated by this technique are showcased in Figure 8[15].

**Fig.8.** An example of Sparsity based image inpainting [14] [15].

**Exemplar Based Inpainting**

The exemplar-based approach is a significant category of inpainting algorithms, which addresses the limitations of PDE-based inpainting and is particularly useful for reconstructing substantial target regions. This approach can be divided into two primary steps. In the first step, priority assignment is performed, followed by the selection of the most suitable matching patch in the second step. By sampling the best matching patches from the known region and seamlessly pasting them into the missing region, this method effectively achieves image inpainting. Additionally, the method fills the structures in the missing regions based on the spatial information of neighboring regions, following a predetermined filling order. Numerous algorithms have been developed for exemplar-based image inpainting, such as the efficient region filling and object removal algorithm proposed by Criminisi[11]. However, it is worth noting that most of the new exemplar-based algorithms adopt a greedy strategy, which can introduce certain challenges related to the filling order or priority. Exemplar-based Inpainting yields satisfactory outcomes exclusively when the absent area comprises uncomplicated structure and texture. Conversely, synthesis of the desired image becomes unattainable if the image lacks an adequate number of samples [12]. An example, shown in Fig. 9, showcases exemplar based image inpainting.

**Fig.9.** An example of Exemplar based image inpainting [16].

## Hybrid Inpainting

The Hybrid Inpainting technique, also known as Image Completion, is employed to fill substantial missing areas in an image. These hybrid methods combine Texture Synthesis and PDE based Inpainting to effectively restore the holes in an image. The underlying concept of these approaches involves dividing the image into two distinct components: one for the Structure region and another for the texture regions. The corresponding decomposed regions are then filled using edge propagating algorithms and texture synthesis techniques. To accomplish Structure completion, a two-step procedure is followed. Firstly, a texture-based segmentation is performed on the input image, and the boundary regions are extrapolated using tensor voting to generate complete image segmentation. Secondly, tensor voting is utilized to synthesize the missing colors. While the tensor voting method is effective in preserving curvature, it faces challenges when dealing with complex structures and the segmentation of natural images, which remain difficult tasks to accomplish [12]. An example, shown in Fig. 10, showcases hybrid image inpainting.

**Fig.10.** An example of Hybrid image inpainting [17].

## Learning Methods

Over the past ten years, there has been a notable rise in computer graphics processing power and the creation of robust image datasets, leading to significant progress in Deep Learning, particularly in the field of computer vision. Consequently, novel data-driven image inpainting methods based on learning have been introduced, surpassing traditional techniques by achieving impressive outcomes with enhanced generalization abilities. Within the realm of Deep Learning, these techniques are classified into two primary categories: Convolutional Neural Network-based methods and Generative Adversarial Network-based methods [31].

## CNN-Based Image Inpainting

In the early days of applying deep learning to image inpainting, Pathak et al. [32] developed a context coder in 2016 by combining the encoder and decoder structure with CNN. This was done to address the challenges faced by CNN, such as the requirement for a significant amount of labeled data and the inclusion of semantic understanding within the incomplete image. The context coder utilized multiple convolution layers within its codec structure, enabling the parametric supplementation of semantic-sensitive content in the image scene. Consequently, it could synthesize high-level features across a wide spatial range, resulting in enhanced features for the nearest neighbor-based inpainting method. This approach marked the first application of CNN in image inpainting [8].

## GAN-Based Image Inpainting

The GAN method, introduced by Goodfellow et al. [33], employs a clever interplay between generative models and discriminant techniques to improve output quality. This approach is illustrated in Figure 11, showcasing the network structure consisting of two key components: the generator G and the discriminator D. The generator G takes in random noise as input and generates synthetic samples that resemble real data. On the other hand, the discriminator D is trained to distinguish between real and fake samples. Whenever D makes accurate judgments, adjustments are made to G's parameters to enhance the realism of the generated data. Conversely, if D makes incorrect judgments, modifications are made to D's parameters to rectify future misclassifications. By considering global information, GAN performs direct feature extraction and image generation on the samples. This streamlined approach leads to shorter generation times, faster speeds, and ultimately, more realistic generated images. The utilization of GAN in image inpainting algorithms has led to the development of an exceptionally efficient generation method, thus establishing its position as a fundamental technique [8].

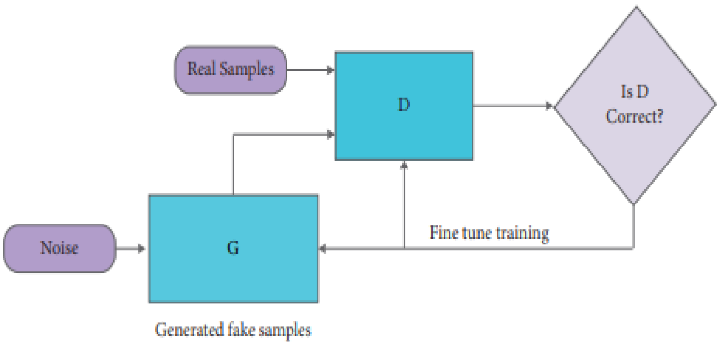


**Figure 11:** The structure of GAN [8].

The application of "image inpainting," a technique designed to substitute missing or damaged parts in an image such as occlusions, holes, and scratches, serves various purposes like artistic creation, object removal, image restoration, and photo editing. Accomplishing image inpainting is a daunting task with several challenges and constraints, greatly influencing its effectiveness and overall quality.

## Data Availability and Diversity

Insufficient and limited data for training and evaluating inpainting models remains a significant challenge in the field of image inpainting. To accurately represent the complexity and variability of real-world images, the majority of the existing datasets are too small, too homogeneous, or too synthetic. For instance, some datasets only include pictures of faces, landscapes, or buildings, which restrict the models' capacity for generalization. Additionally, some datasets create the missing regions using fictitious masks or patterns, which might not accurately reflect real-world instances of image tampering or degradation. In order to provide realistic and difficult inpainting tasks for various domains and applications, there is a need for more diverse and large-scale datasets.

**Consistency in Structure and Semantics**

Ensuring the structural and semantic consistency of inpainted regions with other images is a further challenge for image painting. This means not only that the painted regions must look natural and realistic, but they should also be compatible with the context and content of the surrounding areas. For instance, the inpainting area should not introduce any new objects, distort perspective or infringe physical laws when an object has been removed from an image. In particular, when those missing regions have a high complexity or are situated in major areas of the image, this consistency is difficult to achieve. Some of the existing inpainting techniques use low level features such as pixels, gradients or patches to fill gaps but cannot retain high level features such as shapes, edges and semantics that are essential for visual coherence and clarity.

**User control and feedback**

A third challenge in image inpainting involves granting users the ability to provide input and control over the procedure and its outcomes. The level of flexibility and adaptability required by the inpainting method may vary depending on the user's purpose and preferences. For instance, certain users may desire to specify the location, size, or shape of the missing areas, or adjust the inpainting options and parameters. Others may wish to view intermediate or alternate inpainting results, or refine and modify them after they have been generated. However, many existing inpainting technologies are either fully or semi-automated, lacking any means for user interaction. Additionally, some painting techniques rely on complex Deep Learning models that lack explainability and predictability, failing to provide any justification or explanation for their decisions or painting outcomes.

**Computational efficiency and scalability**

The improvement of the computational efficiency and scalability of image painting techniques is a final challenge. Inpainting techniques have to meet larger, more complex pictures and a growing variety of scenarios that are increasingly diverse and harder to paint with due to increasing demand and expectations for higher quality painting. However, computational costs and time are high for some of the inpainting techniques so they may not be appropriate to applications that take place real-time or on online. In some painting techniques a number of iterations, optimizations or network layers are required to produce inpainted regions which could consume large amounts of memory and processing power. Furthermore, some of the painting techniques are not strong or flexible enough for any type of image resolution, format or field and may need to be modified or refined in order to handle a variety of painting tasks or settings.

## Image Inpainting Tools

There are numerous tools and libraries for image inpainting. Navier-Stokes, Telea, and Fast Marching methods are available through the open source computer vision library known as opencv. It can be used with languages like Python, C++, Java, or others. Python or C++ can be used with pytorch, a deep learning framework that supports partial convolutional neural networks, generative adversarial networks, or context encoders. Professional image editing program Photoshop provides a content-aware fill tool that makes use of machine learning. It can be used with a scripting language or a graphical user interface.

## Image Inpainting Datasets

In order to assess and compare the performance of various inpainting methods, numerous publicly accessible datasets are readily available for the purpose of image inpainting evaluation. The evaluation of each proposed method's effectiveness depends on the image categories they are tested on, encompassing natural images, face images, artificial images, as well as several other distinct categories. ImageNet [18]: The ImageNet dataset is a comprehensive collection of images that serves as a versatile resource. It has been employed in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) since 2010, which has become a renowned standard for evaluating image classification and object detection tasks. This dataset consists of meticulously hand-annotated training images along with a separate set of test images that purposely withhold the manual annotations. The present edition of the ImageNet dataset comprises over 14,197,122 images, out of which 1,034,908 are annotated with bounding box information. CelebA [19]: The CelebFaces Attributes dataset consists of 202,599 face images sized 178×218, featuring 10,177 celebrities. Each image is accompanied by 40 binary labels that indicate various facial attributes such as hair color, gender, and age. FFHQ (Flickr-Faces-HQ) [20]: The dataset known as Flickr-Faces-HQ (FFHQ) comprises a collection of 70,000 top-notch PNG images, each measuring 1024x1024 pixels. This dataset boasts significant diversity in terms of age, ethnicity, and image background. Places [21]: The Places dataset aims to facilitate scene recognition tasks with a vast collection of over 2.5 million images. Encompassing more than 205 scene categories, each category consists of no less than 5,000 images.

CelebA-HQ [22]: The CelebA-HQ dataset is an upgraded version of CelebA, comprising 30,000 images with a resolution of 1024×1024. Places365 [23]: The Places365 dataset is a comprehensive collection of images dedicated to scene recognition. It consists of a staggering 10 million images representing 434 distinct scene classes. The dataset is available in two versions: Places365-Standard and Places365-Challenge-2016. In Places365-Standard, users can access 1.8 million training images and 36,000 validation images spanning across 365 scene classes. On the other hand, the Places365-Challenge-2016 version offers a more extensive training set, with an additional 6.2 million images, incorporating 69 new scene classes. As a result, it provides a grand total of 8 million training images from all 434 scene classes. Fashion-Gen[24]: Fashion-Gen is comprised of 293,008 fashion images captured in high definition (1360 x 1360 pixels), accompanied by meticulously crafted item descriptions offered by seasoned stylists. To ensure thorough showcasing, every item undergoes photography from diverse angles. CASIA V2 [25]: The CASIA V2 dataset has been designed specifically for the purpose of forgery classification. This dataset consists of a total of 4795 images, out of which 1701 are authentic while the remaining 3274 are forged. FDF (Flickr Diverse Faces) [26]: A diverse dataset encompassing human faces with unconventional poses, occluded faces, and a wide range of backgrounds.

Apolloscape Inpainting [27]: The Inpainting dataset is a compilation of paired labeled images and LiDAR scanned point clouds. This dataset is obtained using the HESAI Pandora All-in-One Sensing Kit. The collection process took place in Beijing, China and encompasses diverse lighting conditions and traffic densities. Fingerprint inpainting and denoising [28]: The synthetic training set comprises 168,000 fingerprint images, consisting of 84,000 fingerprints with two impressions per fingerprint - one ground-truth and one degraded. Similarly, the synthetic test set comprises 16,800 fingerprint images, containing 8,400 fingerprints and two impressions per fingerprint - one ground-truth and one degraded. On the other hand, the real test set consists of a total of 1,680 fingerprint images. This set includes 140 fingerprints, with each fingerprint having 12 impressions. These impressions are high-quality scans obtained under operational conditions.

PAL4Inpaint [29]: PAL4Inpaint is an extensive dataset, comprising 4,795 image inpainting outcomes. This dataset has been meticulously annotated with per-pixel perceptual artifacts, specifically created for facilitating image inpainting tasks. Unsplash_1k (Unsplash_1k_crops) [30]: The Unsplash-Lite Dataset comprises 25k nature-themed photos of high resolution. Each image in the dataset is resized and cropped to 1024x1024 dimensions. Furthermore, a series of masks is created utilizing thin, medium, and thick brush strokes, following the methodology explained in LaMa. The aim of this dataset is to function as a test-set for assessing the performance of inpainting techniques on natural images with high resolution.

## III. Conclusion

The primary objective of this paper is to offer a comprehensive understanding of diverse approaches employed in image inpainting. Image inpainting involves utilizing various techniques to substitute the absent or corrupted portions of image data. The research delves into the examination of different methodologies for image inpainting, including classical image inpainting and deep learning-based image inpainting techniques. Each method is accompanied by a detailed explanation of the inpainting process, along with its respective advantages and disadvantages. Additionally, this paper delves into an assortment of datasets, in addition to outlining the challenges and limitations associated with image inpainting techniques.

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