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Nermin Mohamed Fawzy Salem PhD
Electrical Engineering Department - Future University in Egypt, nfawzy@fue.edu.eg

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A Survey on Various Image Inpainting Techniques

*Nermin M. Salem **

Electrical Engineering Department, Future University in Egypt, Cairo, Egypt: nfawzy@fue.edu.eg

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ABSTRACT

Over the decades' researchers have studied the image inpainting problem intensively due to its high significance and effectiveness in various image processing applications such as people and object security, object removal, face editing applications. Image inpainting is defined as the process of completing or removing a missing region in images. It is considered one of the most challenging topics in the image processing field, although, it requires a deep understanding of the image details in terms of texture and structure. In this paper, a survey of most image inpainting techniques is presented and summarized with comparisons including the merits and demerits of each technique which could help researchers in evaluating their proposed techniques against.

1. Introduction

Image inpainting refers to the process of filling/completing missing regions across images with an estimated prediction according to the surrounding pixel information, it is a branch of image processing (Pushpalwar, R.T. and Bhandari 2016). 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 (Pillai and Khadagade 2017), image editing (Guillemot and Meur 2014), removal of the unwanted object (Lakshmanan and Gomathi 2017), image denoising, and much more. Some different applications of image inpainting are shown in Fig. 1.

The resultant reconstructed image should preserve and maintain the edge information of the real image. Many techniques have worked on the fact that both known and unknown image pixels share the same statistical parameters and geometrical structures which leads to better visual recovered images (Zeng, et al. 2019) (Guillemot and Meur 2014). Image inpainting can be categorized into two main categories: Traditional techniques and deep learning techniques. Traditional methods employed either diffusion-based approaches that generate local structures into the missing parts, or exemplar-based approaches that fill the missing part's one pixel/patch at a time while preserving the consistency with the surrounding pixels.

* *Corresponding author.* Tel.: +2 010 92 999 343 - *Electrical Engineering Department, Future University in Egypt, Cairo, Egypt*.
E-mail address: *nfawzy@fue.edu.eg*

Fig. 1 - Different applications for image inpainting. (a) Image restoration (Zarif, Faye and Rambli 2014), (b) Object Removal (A. Criminisi 2004) , (c) Restored painting and frame (Ven and Tan 2012).

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 (Elharrouss, et al. 2019). This was the motivation for researchers to further investigate and find other methods for dealing with such a problem. Recent methods employ deep learning (Pathak, et al. 2016) for solving the complex task of image inpainting because these methods have shown excellent results for image inpainting over the past years. The complexity of image inpainting comes from its' need to fully understand the image's structure, texture, and color data to be able to produce natural images.

2. Traditional Image Inpainting Algorithms

Most of the well-known traditional image inpainting algorithms that do not use deep learning methods will be discussed in this category. These algorithms can be further sub-categorized into the following five sub-categories:

- Diffusion-Based Inpainting
- Texture Synthesis
- Exemplar-Based Inpainting
- Hierarchical Super-Resolution Based Inpainting
- Spatial Patch Blending Inpainting

2.1. Diffusion-based algorithms

These techniques (Guillemot and Meur 2014) are considered to be one of the first algorithms to approach the problem of image inpainting. These algorithms are mainly dependent on the use of the variation method and the Partial Differential Equation (PDE). They work by completing/filling the missing region by smoothly propagating the content of the image from the surrounding region into the target region. The pioneer work in this field had been presented in (Bertalmio, Sapiro, et al. 2000) which presented a training model using non-linear PDEs to resemble the technique used by artists specialized in the restoration of paintings used in museums. This technique generates information towards isophotes. However, this technique leads to blurry images and suffered from the presence of artifacts around the recovered region.

An energy minimization technique for computing the inpainted recovered image through a coupled non-linear differential equation was presented in (Ballester, et al. 2001). Another technique worked on the link between isophote direction and the Navier-Stokes equation (Bertalmio and A.L. Bertozzi, Navier-Stokes, Fluid Dynamics, and Image and Video Inpainting 2001). This observation inspired the authors to present a solution using the transport equation for the missing domain filling. A two-step algorithm in (Tai, Osher and Holm 2006) where in the first step, an initial construction for the missing regions were produced by solving the non-linear Total Variation (TV)-strokes equation for finding the isophote directions for these regions. In the second step, the image is restored so that it can be adapted to the construction produced from the first step. A modification for the method used in (Tai, Osher and Holm 2006) was presented in (Meur, Gautier and Guillemot, Examplar-based Inpainting based on Local Geometry 2011). This method combines a PDE-based technique with exemplar-based where a structure tensor for priority computing of patches is used for inpainting. The PDE approach propagates, i.e., diffuses, the local information of the image surrounding region into the missing hole as presented in Fig. 2.

Another diffusion-based algorithm in (Li, Luo and Huang 2017) employed the localization of the diffusion-based inpainted recovered regions in images. First, they analyzed the diffusion operation of inpainting and then observed the Laplacian image changes to distinguish between the inpainted and real/actual regions of the image. This analysis is used to obtain a representation of features based on the intra-channel and inter-channel local variations of the changes to recognize the inpainted recovered regions. Another diffusion-based algorithm in (Li, et al. 2016) based on the computing of the exploiting diffusion coefficients considering the direction and distance between the damaged pixel and its neighborhood pixel. One more diffusion-based algorithm in (Sridevi and Kumar 2019) presented a mathematical model that is derived from using fractional-order derivative and Fourier transform to remove text, noise, and blur in images.

Fig. 2 - Diffusion of local information (Shivaranjani and Priyadharsini 2016).

In summary, PDE approaches have different forms such as linear, non-linear, isotropic, i.e., the same diffusion for each direction, and anisotropic, i.e., varying diffusion with respect to direction. However, the major drawback of the PDEs techniques is that they usually suffer from blurred results especially in the case of large missing holes inpainting. PDE-based approaches are appropriate for the completion of completing lines, curves, and small simple missing regions (Shivaranjani and Priyadharsini 2016).

2.2. Texture Synthesis Techniques

Texture techniques (Chavda and Gagnani, Survey on Image Inpainting Techniques: Texture Synthesis, Convolution and Exemplar Based Algorithms 2014) are also considered to be one of the early techniques used to solve the image inpainting problem (Criminisi, Pérez and Toyama 2004). The notation of patches was first introduced with these methods. Texture synthesis techniques use pixel information from the surrounding neighborhood in a random manner to fill the missing hole in images. i.e., to pick existing pixels from the same image with similar neighborhoods. Texture synthesis techniques produce good results for inpainting small missing regions in simple structure images; however, these techniques are relatively slow since the filling process is done in pixel-style. These algorithms maintain the structure of images as shown in Fig. 3. This occurs by including the input of known pixels while completing the missing hole. Texture synthesis algorithms have a simple concept, their idea is to borrow or copy patches from the surrounding neighborhood to inpaint the missing hole. This results in a consistently recovered image.

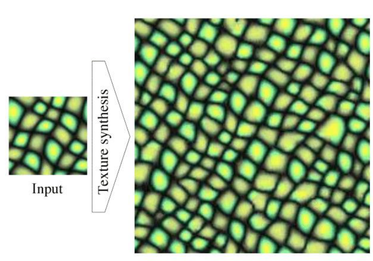

Fig. 3 - Texture Synthesis (Shivaranjani and Priyadharsini 2016)**.**

A combined texture synthesis technique in (Wang 2011) also divides the image into a cartoon image and a texture image. Afterward, it uses a boundary restoration for inpainting the structure image and texture synthesis for inpainting the texture image. This method showed good results for inpainting texture images with a similar structure, but it could not produce the same good results if the curvature of the boundary is variable, i.e., complex unrepeated structure.

An image inpainting algorithm (Casaca, et al. 2014) also combining texture synthesis, transport equation, anisotropic diffusion, and a sampling technique to reduce the inpainting process computational cost. Consider an image with a missing region, initially, a cartoon image is generated using anisotropic diffusion, then a block-based inpainting method is used to combine the cartoon image generated and a measure derived from the transport equation to indicate the priority of pixels to be filled. Next, a sampling region is dynamically generated to preserve the propagation of edges towards the structures of the image to avoid redundant searches during the filling process. Afterward, a cartoon-based metric is calculated to measure the similarity between the target and generated blocks. This method showed a good performance; however, it has some limitations such as parameter tuning and unpleasant results in the case of inpainting non-textured images with color variation.

In summary, texture synthesis is suitable for inpainting nature images with similar textures without complex objects as presented in (Criminisi, Pérez and Toyama 2004) and (Efros and Leung 1999). These algorithms are also considered to be slow algorithms. This can be justified by the fact that the filling process is done in a pixel-wise manner. Texture synthesis algorithms are suitable for the inpainting of small missing regions with repeated or plain texture images.

2.3. Exemplar-Based Image Inpainting

Exemplar-based techniques (Meur, Gautier and Guillemot, Examplar-based Inpainting based on Local Geometry 2011) and (Chavda and Gagnani, Survey on Image Inpainting Techniques: Texture Synthesis, Convolution and Exemplar Based Algorithms 2014) were motivated by texture synthesis algorithms, which can also be referred to as patch-based techniques. Exemplar-based algorithms are one of the popular image inpainting techniques. They are used to produce better results than diffusion-based techniques. The inpainting process fills the missing region from the neighbour surrounding pixels within the same patch (Ogawa and Haseyama 2013) and (Awati 2016).

This technique can inpaint relatively larger missing holes than previously discussed techniques. Generally, Examplar-based techniques are a two-step technique; they are

- Priority Allocation as the first step
- The choice of the best candidate patch as the second step

The inpainting process goes as follows: A selection of the best patches from the surrounding neighbourhood area around the missing hole is performed. This selection process is computed through a priority assignment for each of the surrounding patches in the first step, and then these patches are used in the filling of missing patches according to the predefined priority as studied in (Criminisi, Pérez and Toyama 2004), (Daisy, et al. 2014) and (Wong and Orchard 2008). However, the most critical issue in these techniques is how to find the best patch that looks like the target missing patch. Therefore, to fill out a missing patch, it searches the nearest neighbors patches and borrows one to fill the target missing hole in descending priority order.

In summary, examplar-based techniques are an iterative approach which works as follow:

- Target region initialization: Colors the target region with an initial color for distinguishing the missing hole from the rest of the image
- Priorities computations: Computes a priority function for priority assignment for all missing patches at the beginning of each iteration
- Select the best candidate patch: The patch with the most similar matching patch form a real image to fill the missing area
- Update the missing area after each iteration until the missing area is totally filled

An inpainting technique presented in (Criminisi, Pérez and Toyama 2004) combines texture synthesis and inpainting techniques. This technique employs texture synthesis and orders the filling region with respect to a priority assignment approach. This technique succeeded in object removal in images with similar repeated textures as shown in Fig. 4.

The authors presented a two-step image inpainting technique in (Criminisi, Pérez and Toyama 2004):

- Texture synthesis: To generate large image regions from sample textures of the same image
- Inpainting approach: To fill in small image gaps within the image

The main problem with this technique is to decide the order of patches to be filled. For this issue, the authors implement a best-fit algorithm in which the propagation of the synthesized pixels is performed in the same manner as the information propagated in inpainting and they used exemplar-based synthesis for actual color calculations.

Fig. 4 - Large object removal in similar texture images (Criminisi, Pérez and Toyama 2004). (a) The real image on the left; (b) The recovered image on the right.

An A-weighted similarity function using non-local means has been introduced in (Wong and Orchard 2008). This weighted function works with multiple patches from the surrounding areas to the missing region for filling it up. The non-local information from different image samples was used to improve the naturalness of images along with the exemplar-based technique. This method produced good visual quality and non-blurred visually plausible images. The results prove that this method can provide good inpainting results for small regions with simple texture images.

An inpainting method in (Liu, et al. 2018) operated on the statistical regularization and similarity between the image regions to pull out the dominant linear structures of the selected target regions. Then there is a reconstruction of the missing regions using the Markov Random Field model (MRF). This method showed good results in the removal of objects as shown in Fig. 5.

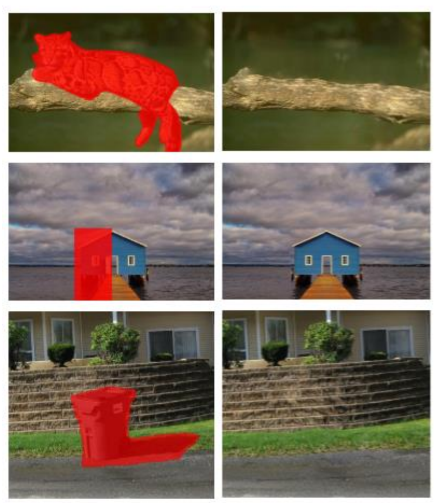

Fig. 5 - Inpainting results of the image inpainting method of (Liu, et al. 2018).

A patch-based method (Ding, Ram and Rodríguez 2018) employed both the nonlocal texture similarity and the local smoothness intensity were used by the authors for solving the image inpainting problem. Gaussian-weighted non-local texture similarity measure was also used to achieve various candidate patches for each target patch. They also applied the α-trimmed mean filter for the computation of the pixel intensity for different patches. Another patch-based inpainting technique (Zeng, et al. 2019) improved the poor performance of the inpainting algorithms based on separated priority as it could easily misguided in searching for the candidate patches. This leads to inconsistent propagation of the texture and structure of the edges. Saliency mapping and gray entropy were presented as a solution. In the priority phase, saliency mapping was used to ensure that regions with strong structure information and visual importance are both completed precisely. The best candidate patch is selected based on the color information and the computed saliency features. Gray entropy is used to control the search for a patch. A patch-based filling mechanism according to the direction of image structure (Chen, et al. 2021). A priority term had been redefined to eliminate the product effect and ensure data term had always effective. This priority of patch repairing, and the best matching patch are determined by the similarity of the known information and the consistency of the unknown information in the repairing patch.

2.4. Hierarchical Super-Resolution Based Inpainting

Although the exemplar-based method was one of the most common widely used techniques, these techniques have suffered from several problems such as the patches filling order and patch size. A novel-based framework for inpainting using an exemplar-based method in (Meur, Ebdelli and Guillemot, Hierarchical Super Resolution-based Inpainting 2013). First, a coarse instance of an input image followed by a hierarchical super-resolution update is used to retrieve the details of the missing hole, as it is always easier to paint a low-resolution image than a high-resolution image. Samples of the results of the algorithm are shown in Fig. 6.

Fig. 6 - Hierarchical super-resolution-based inpainting results (Meur, Ebdelli and Guillemot, Hierarchical Super Resolution-based Inpainting 2013). (a) The real image on the left; (b) The recovered image on the right.

The algorithm works as follows:

- The input image resolution is downsampled
- The missing holes in the low-resolution image are filled using dictionary building and similarity calculations
- Recover the image to its real resolution

2.5. Spatial Patch Blending Algorithm

It is an image inpainting technique suitable for any type of hole pattern that was presented in (Daisy, Tschumperlé and Lezoray 2013). It is a fast and general technique used in artifacts reconstruction without affecting the inpainted image. Artifacts are defined as variations in brightness or color.
It is also a two-step technique:

- Detection of the artifact
- Spatial patch blending

The reconstruction operation is performed equally in all isotropic directions instead of using a single patchwork. Spatial patch blending reduces the joint between pixels within patches as parts of these patches can be ignored, i.e., while containing useful information, if the order of filling is done differently. This method is a pixel-wise process where a group of overlapping patches is extracted for each pixel, followed by a gaussian weighting function. This weighting function is defined by the policy of blending patches. The main drawback is the large computation time and memory usage of the missing hole size. This could be explained by the fact that there is an algorithm that must compute various distance maps for the reconstructed patches. These maps are then merged by nearby patches so that the borders of the missing hole became invisible. The results are shown in Fig. 7.

The advantage of this algorithm is that it removes inconsistent patches while trying to maintain the texture and structure of the images and it is highly affected by patch size. An enhancement algorithm was implemented to overcome the use of computation and memory usage compared to the original algorithm. Most of the traditional image inpainting techniques relied on the use of local diffusion information only for filling the missing area in images. However, this was also the main drawback of these techniques. Local information should not only be considered for understanding the structure and texture of the missing region as it results in the production of inconsistent recovered regions that are inconsistent with the overall image. Most known traditional image inpainting algorithms have been summarized in Table 1, showing the inpainting technique used and evaluation of its' performance.

Fig. 7 - Fast Spatial Patch Blending Algorithm Results (Daisy, Tschumperlé and Lezoray 2013). (a) The real image on the left; (b) The recovered image on the right.

Table 1 - Traditional image inpainting techniques.

Paper Title	**Image Inpainting used Technique**	**Merits**	**Demerits**
Guillemot et al (2014), Image Inpainting: Overview and recent advance	Diffusion-Based	• Simple • Adjusts well for small size missing regions	• Blurry results in case of large size missing regions • Not applicable to the filling of textured regions
Haodong Li et al (2017), Localization of diffusion-based inpainting in digital images	Diffusion-Based	• Adjusts well for simple structure images	• Fails at recovering textures
Kangshun Li et al (2014), Image inpainting algorithm based on tv model and evolutionary algorithm	Diffusion-Based	• Simple • Easy to implement	• Generates blurry results for complex structure regions
G. Sridevi et al (2019), Image inpainting based on fractional-order nonlinear diffusion for image reconstruction	It is a combination of Texture synthesis and Exemplar-Based image inpainting.	• Eliminate staircase and speckle effects for recovered regions	• Fails at handling any curved structure regions • Works on Grey images
Criminisi et al (2004), Region Filling and Object Removal by Exemplar-based Image Inpainting	Texture-Based	• Simple • Remove unwanted patterns • Use local and global features	• Generates blurry regions
Sangeetha K et al (2011), Combined Structure and Texture Image Inpainting Algorithm for Natural Scene Image Completion	Texture-Based	• Performs well for similar structure images • Simple	• Fails when the curvature of the object is variable
Minqin Wang (2011), A Novel Image Inpainting Method based on Image Decomposition	Texture-Based	• Object removal technique • Effective to inpaint texture image with complex structure	• Limited by the parameters tuning • Fails when images have non-textured color variation • Generates blurry images
Wallace Casaca et al (2014), Combining anisotropic diffusion, transport equation, and texture synthesis for inpainting textured images	Texture- Based	• Performs well • Flexible	• Fails when inpainting non-textured images with color variation
Alexander Wong et al (2008), A Nonlocal-means Approach to Exemplar-based Inpainting	Patch-Based image inpainting	• Performs well for text, object, and scratch removal. • Easy to implement	• Works with grey images • Works with small regions such as scratches • Require high computation

K. Jin et al (2015), Annihilating Filter-Based Low-Rank Hankel Matrix Approach for Image Inpainting	Patch-Based using Annihilation property filter, low rank structured matrix	• Performs well for small size regions • simple	• Generate blurry results for large size regions
T Ružić et al (2014), Context-aware patch-based image inpainting using Markov random field modeling	Patch-Based using MRF	• Performs well in inpainting applications like scratch, text, and object removal • Simple • Efficient	• Fails when the block similarity threshold is high
J Liu et al (2018), Structure-guided image inpainting using homography transformation	Patch-Based using MRF	• Performs well for smooth objects	• Generate blurry results for large size regions • Presence of artifacts around the inpainted regions
I D Ding et al (2019), mage inpainting using nonlocal texture matching and nonlinear filtering	Patch-Based Nonlocal Texture Matching, Nonlinear Filtering (α-trimmed mean filter)	• Performs well when inpainting large missing regions in images with texture and geometric structures. • Preserve the edges information	• High computational complexity
J Zeng et al (2019), Image inpainting algorithm based on the saliency map and gray entropy	Patch-Based Saliency Map and Gray entropy	• Better visual effects for small size missing region • Efficient • Simple	• Generate blurry results for large size regions
O Le Meur et al (2013), Hierarchical Super-Resolution-based Inpainting	Hierarchical Super Resolution	• Efficient • Simple • Preserve context and texture in images	• Require high computational cost • Failed at curved structures
M Daisy et al (2013), A Fast-Spatial Patch Blending Algorithm for Artefact Reduction in Pattern-based Image Inpainting	Spatial Patch Blending Algorithm	• Faster execution • Performs well for simple structure images	• Generate blurry results for large size regions • Not applicable to the filling of textured regions

3. Deep Learning Image Inpainting Algorithms

Deep learning approaches have provided a much more accurate and impressive solution to the problem of image inpainting. Due to its superior results, many researchers are encouraged to update, use, or even implement new approaches. Deep learning approaches such as Convolution Neural Networks (CNNs) had been adapted for image inpainting. The idea was to train the CNNs using a training set of images for filling/completing the missing areas/regions in images. The earliest solution for tackling image inpainting was to train a dedicated model to inpaint a missing hole with a specific location across images.

Training CNNs usually require an input pair consisting of the real image, i.e., also known as Ground Truth image (GT), and the masked image, i.e., the image with the missing area. The training operation begins by training the network to complete that missing region then hopefully the trained model could be used for any other images, i.e., not included in the training set, or even generally for images with different missing areas in terms of shape and size of that missing hole.

The deep learning image inpainting category can be further sub-categorized into two main sub-categories:

- Algorithms that did not use Generative Adversarial Network (GAN): **Non-GAN-Based Systems**
- Algorithms that used Generative Adversarial Network (GAN): **GAN-Based Systems**

3.1. Non-GAN-Based Systems

Several algorithms have been implemented for solving the important problem of image inpainting. In this Subsection, the algorithms used by traditional CNN will be discussed and presented. The authors presented in (Cai, et al. 2015) a blind image inpainting technique that employed a fully CNN trained with an input pair composed of GT and masked images. The model is called Blind Inpainting Convolutional Neural Network (BICNN). After training, the training model could be used to detect the missing area and then inpaint this region. An approach designed for images with lower resolution is presented in (Xie, Xu and Chen 2012). The authors used a sparse algorithm along with a denoising Auto-Encoder (DA) pre-trained model. The model is called Stacked Sparse Denoising Auto-Encoders (SSDA). SSDA is a blind algorithm that deals with the overlapping patches from the image as data objects. During training, the model is provided with both the corrupted image patches x_i, i.e., noisy image patches, for i = 1,2,…., N, and the Ground Truth patches y_i. SSDA will rebuild and produce a recovered image without any noise. This approach did not deal with any of the RGB images as (Cai, et al. 2015), only greyscale images.

An energy-saving algorithm in (Kerzhner, Alad and Romano 2018). This minimizes the distance between the GT and the masked image. Initially, linear interpolation was used to create an initial inpainted hole followed by the use of a pre-trained classification model to fill the hole using an image with the average score for its detected class. The pretrained model for the ImageNet classification is used for image inpainting (Fawzi, et al. 2016). This technique is a two-step approach in which the image associated with the maximum class score is first searched. This is considered to be the initial hallucination/prediction of the missing hole. This initial prediction is followed by a built-in graph-based regularizer for smoothing the results in the second step. This algorithm has produced good results for simple images that have no complex structure. An image inpainting technique for inpainting random missing holes based on partial convolution in (Liu, et al. 2018). The main idea was to limit the convolution to only the valid pixels. They performed a mask-update step on each layer. They used perceptual loss (Li, et al. 2017), style-loss (Johnson, Alahi and Fei-Fei 2016), and total variation (TV) loss (Getreuer 2012) as a joint loss measure. Unequal weights for these losses were used by conducting a hyperparameter search on 100 images from the validation set. Unfortunately, this approach has several problems such as its high complexity in gating an un-learnable layer, when multiplying it with inputs feature map. Partial convolution also limits each pixel position into valid or invalid and finally causing the fade of valid pixels eventually in deep layers. The results are shown in Fig. 8.

Fig. 8 - Partial convolution Results (Fawzi, et al. 2016). (a) The masked image on the left; (b) The recovered image in the middle; (c) The real image on the right.

A multiscale patch algorithm in (Yang, et al. 2017) was implemented for a high-resolution method based on the initial trained model of (Pathak, et al. 2016). This algorithm dealt with 512×512 images with a center missing region of size 256×256. It is a two-step technique:

- In the first step, initial inpainted images with lower resolution are generated
- In the second step, the generated image is updated by the joint loss function, which is composed of texture loss, content loss, and finally a total variation (TV) loss

Content loss is responsible for measuring the pixel-wise loss of L2 between GT and the recovered image produced. The texture loss is calculated by comparing patches from inside and outside the missing area. It gives good results for symmetrical images around the center. However, this is a slow algorithm due to the many iterations needed.

3.2. GAN-Based Systems

Although Convolution Neural Networks (CNNs) showed significant improvement in the image inpainting problem. CNN still has major problems. The goal is to train a CNN is to minimize an objective loss function. This function is usually calculated by measuring the Euclidean distance between the recovered inpainted pixels and the Ground Truth pixels. This loss measure usually tends to produce blurry images (Pathak, et al. 2016) and (Zhang, Isola and Efros 2016). This can be simply explained by the fact that the Euclidean distance is minimized by taking the average of all outputs which leads to blurry outputs. Image inpainting aims to produce a natural realistic image that contradicts the current situation. Therefore, we need a catalyst to help with the blurry results. Generative Adversarial Network (GAN) (Goodfellow, et al. 2014) is used to solve this challenging problem. GAN is a synthesis trained model based on a comparison of real images with the generated images. Afterward, GANs became a motivation for many researches such as (E. Denton, et al. 2015), (Radford, Metz and Chintala, Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks 2016), (Salimans, Goodfellow, et al., Improved Techniques for Training GANs 2016), and (Zhao, Mathieu and LeCun 2017). Employing GANs along with CNN solved the blurry output problem by applying a loss function called adversarial loss (Adv loss) that automatically adapts to data.

GANs always consists of two main networks, each with a specific role and competing against each other:

- Discriminator: D
- Generator: G

Both discriminator and generator are parametric functions, where, the generator G maps the latent space noise vector z into an image x where: G(z) → x and the discriminator D grades the image according to D(x) → [0,1]. The learning procedure of GAN can be considered as a two-player game, the discriminator is responsible for distinguishing between forgeries and authentic images, i.e., fake and real images. The generator is responsible for producing fake images that look like the real ones to fool the discriminator. Both the generator and the discriminator are jointly trained competitively. This allows the generator to generate plausible images. Only one network parameter is updated during training. When the generator G is fixed, the discriminator D is trained to differentiate between fake and real images. When the discriminator is optimal, it may freeze so that the generator can be trained to achieve a minimal discriminator loss.

When the generator reaches the same distribution of real data, this situation confuses the discriminator that causes it to predict 0.5 for all inputs (Goodfellow, et al. 2014). This means that the discriminator can no longer distinguish fake images from real images. Practically, the discriminator can be trained until it is optimal.

GAN procedure can be summarized into the following steps:

- The generator generates an image
- This generated image is fed to the discriminator with various images taken from the real, actual training dataset
- The discriminator takes in both real and fake images and returns a decision as a probability, i.e., a number between 0 and 1, where 0 represents the prediction of a fake image and 1 representing the prediction of the real image

To train a GAN, a value function V(G, D) is computed according to both the generator and discriminator. The aim is to $\min_{G} \max_{D} V(G, D)$, where $V(G, D)$ can be computed from the following Equation:

$$\mathrm{V(G,D)} = E_{x\in X}\,[log\,D(x)] + E_{z\in Z}[log(1 - D(Z))] \qquad (1)$$

where V(G, D) is the adversarial loss, X is the real data, and Z is the latent space.

The training procedure of GAN can be considered as a two-player game due to the successive training competition between the two networks. This gives the generator the ability to produce plausible inpainted images. The structure of the GAN is shown in Figure 9. The impressive results of GAN motivate a lot of research for implementing different variants of GAN. Practically, GAN training is a challenging task as it is often unstable for lots of reasons (Radford, Metz and Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks 2016), (Salimans, Goodfellow, et al., Improved techniques for training gans 2016), and (Arjovsky and Bottou 2016) such as networks convergence is hard to achieve, GANs can easily get into a collapse mode, i.e., the generator generates similar images for various noise vector z. Various improvements for GAN were implemented for more stable training.

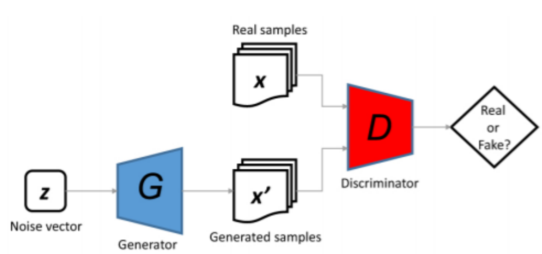

Fig. 9 - GAN structure (Wu, Xu and Hall 2017)**.**

An improvement for GAN in (Mirza and Osindero 2014). It was referred to as conditional Generative Adversarial Networks (cGANs) as it extends GANs with a conditional model. This conditional model can be established by feeding the data w desired to condition on both generator and discriminator, i.e., both of them are conditioned on some additional information. This additional information could be sketches, text, or even class labels. cGANs provide additional control over the data generated which is not the case with the original GAN. Fig. 10 shows the structure of cGAN.

The objective function of cGAN can be expressed by the following Equation:

$$\min_G \max_D V = E_{x\in p_{data}(x)}[\log D(x|y) + E_{z\in p_z(z)}[\log(1 - D(G(z|w)))] \quad (2)$$

where w is the auxiliary information, $p_z(z)$ is the noise input, and x is the real data, both x and w are presented as inputs for the discriminator.

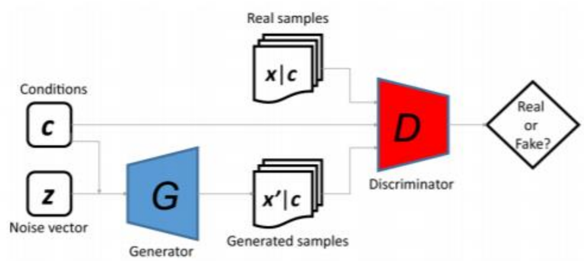

Fig. 10 - cGAN structure (Wu, Xu and Hall 2017)**.**

A further improvement for GAN in (Radford, Metz and Chintala, Unsupervised representation learning with deep convolutional generative adversarial networks 2016). It is called Deep Convolutional Generative Adversarial Networks (DCGANs) for unsupervised learning. The authors provided a set of constraints in the GAN architecture for both generator and discriminator for a more stable training.

These GAN architectural constraints are as follows:

- All pooling layers for the discriminator are replaced with stride convolutions and those of the generator are replaced by fractional-strided convolutions to allow the network to acquire/learn its spatial downsampling
- Batchnorm layers are used for both generator and discriminator
- All fully connected hidden layers are removed
- Tanh is used as an activation function for the generator, while Rectified Linear Units (ReLU) activation is used for other layers
- Leaky ReLU activation function is used for the discriminator

DCGANs are more stable in training and can produce higher quality images and it is used in many applications. Another improvement for GAN in (E. L. Denton, et al. 2015). It is called Information Processing Systems (LAPGAN). It is composed of a cascade of convolutional networks inside a Laplacian pyramid framework to produce images in a coarse-to-fine fashion. The Laplacian pyramid can be defined as a linear invertible image representation that has a set of band-pass images with a low-frequency residual. A separate generative content model for each level of the pyramid is trained using the basic GAN approach (Goodfellow, et al. 2014). A basic GAN is trained to map a noise vector z to an image with the coarsest resolution. For each level k of the pyramid, i.e., $0 \le k \le K$, a separate cGAn is used in training constrained by the output image in its coarser level. LAPGANs can produce higher resolution images.

A newer version of GAN in (Demir and Unal 2018) and (Isola, et al. 2018). They presented a simple yet effective network that can easily adapt to the various structures of the missing regions. PatchGAN is used to allow the discriminator to run differently from the traditional GAN, i.e., works on patches rather than the whole image, to classify whether each $N \times N$ patch of the image is real or not instead of the whole image. This discriminator (D) runs consecutively across the whole image, averaging all patches outputs to provide only one output of D. The authors presented an image inpainting algorithm based on the generative adversarial network framework (Demir and Unal 2018). A PGGAN approach would combine the traditional GAN with the PatchGAN approach. Their goal was to measure the quality of the images in terms of patches as well as the whole image. The authors designed a weight-sharing architecture at the first beginning layers of the training network to be able to learn common low-level features.

The network architecture consists of two cascaded paths:

- The first path to decide whether the whole image is real or fake
- The second path is to decide the local patches as the PatchGAN

These two paths are connected by fully connected layers. This approach presents a good objective function for the evaluation of the naturalness of the generated images as shown in Fig. 11.

Fig. 11 - Samples of PGGAN recovered images (Demir and Unal 2018)**.**

A modified discriminator in (Isola, et al. 2018) using a convolutional PatchGAN classifier. This classifier only deals with the scale of the patches' structure. They restricted the modified discriminator to model only the high-frequency structure through an L1 loss to force low-frequency correctness. By this restriction, PatchGAN can only grade the structure of patches followed by running the discriminator convolutionally through the whole image, averaging all scores to generate the ultimate score of the discriminator. The results are presented in Fig. 12.

The first GAN-based image inpainting methodology in (Pathak, et al. 2016). It was a new novel-based approach dedicated to image inpainting. They used a context encoder for filling the missing hole, i.e., a square missing area located in the center of images, based on the adjacent surroundings of the missing area as well as the context of the entire image. For this purpose, they used a joint pixel-wise loss measurement consisting of L2 reconstruction loss and adversarial loss (Adv loss). Each of the two losses has been used for a specific purpose:

- L2 reconstruction loss is responsible for capturing the images entire structure
- Adv loss is responsible for giving a realistic look for the output image

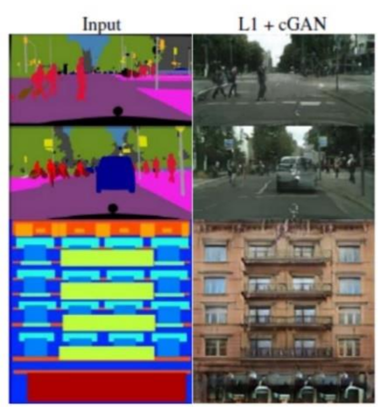

Fig. 12 - PatchGAN results (Isola, et al. 2018). (a) Input image on the left; (b) The recovered image on the right.

The results were acceptable for a center-square missing region across images. However, it failed to perform well in case of random shaped missing regions. A semantic image inpainting technique using adversarial loss and self-learning encoder-decoder model in (Salem, Mahdi and Abbas, Semantic image inpainting using self-learning encoder-decoder and adversarial loss 2018). A good image restoration method demands to preserve the structural consistency and texture clarity. Another GAN-based method for random-shaped missing regions with variable size and arbitrary locations across the image in (Salem, Mahdi and Abbas, Random-Shaped Image Inpainting using Dilated Convolution 2019). Dilated convolutions for composing multiscale context information without any loss in resolution as well as including a modification mask step after each convolution operation. This method also includes a global discriminator that also considers the scale of patches as well as the whole image. The global discriminator is responsible for capturing local continuity of images texture as well as the overall global images' features. The results are shown in Fig. 13.

Fig. 13 - Results of the inpainting method (Salem, Mahdi and Abbas, Random-Shaped Image Inpainting using Dilated Convolution 2019). (a) The real image on the left; (b) The masked image on the middle; (c) The recovered image on the right.

Another GAN-based algorithm was introduced in (Iizuka, Simo-Serra and Ishikawa 2017) to consider both global and local image inpainting. The model used an input pair, consisting of the GT image and binary mask, to indicate the location and size of the missing holes. This input pair is used to produce the masked image that is passed through the network for producing an output image with that similar resolution as the input image.

The network is composed of three networks:

1. Generator Network
2. Local Discriminator
3. Global Discriminator

The generator is a simple Encoder-Decoder pipeline that uses both dilated convolution (Yu and Koltun 2016) and standard convolution for the rest of the layers. The local discriminator selects a small region containing the required hole to be filled while the global discriminator considers the overall image. The final output image is therefore consistent in terms of local and global scales. The work produces good results for images with missing random-square holes, as shown in Fig. 14.

Fig. 14 - Globally and Locally Results (Iizuka, Simo-Serra and Ishikawa 2017). (a) Upper row: masked images; (b) bottom row: recovered images.

Another iterative GAN-based approach for image inpainting is (Yeh, et al. 2017). The authors trained a GANs generator G to maps a latent vector z of an image to produce a recovered z* image with minimized loss measure consisting of Adv loss and content loss. Weighted pixel-wise L1 loss is used for content loss. It is a back-propagation approach used for inpainting faces. The results are shown in Fig. 15.

Fig. 15 - Face inpainting (Yeh, et al. 2017) . (a) The real image on the left; (b) The masked image on the middle; (c) The recovered image on the right.

A GAN-based method for face inpainting was presented in (Li, et al. 2017). the same network architecture presented in (Iizuka, Simo-Serra and Ishikawa 2017) with global and local discriminator cooperation was used along with a pre-trained parsing network for better coherent output images. The results are shown in Fig. 16. Edgeconnect (Nazeri, et al. 2019) is a technique for edge generators for filling the missing regions in images. This technique shows natural recovered images but it requires high computational complexity and memory usage.

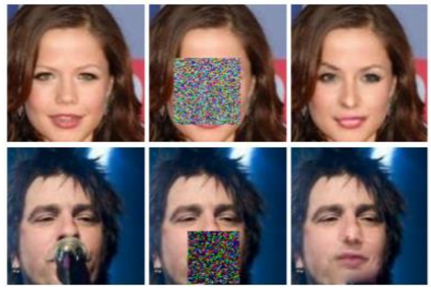

Fig. 16 - Enhanced face inpainting results (Li, et al. 2017) . (a) The real image on the left; (b) The masked image on the middle; (c) The recovered image on the right.

Two-image inpainting techniques in (Nadim and Jung 2020) using a mask pruning-based global attention module and a global and local attention module to obtain global dependency information and the local similarity information among the features for refined results. They produced very promising good results however, they could not maintain and preserve human identity in images. A face inpainting approach in (Salem, Mahdi and Abbas 2021) succeeded in preserving and maintain human identities for humans in images by using Histogram of Oriented Gradients (HOG) features as guidance to the inpainting process.

The model composed of two-cascaded networks, both networks employed Encoder/Decoder architecture:

1. Face-shape predictor: To generate and train the network with the Histogram of Oriented Gradients (HOG). This is the guidance network.
2. Image inpainting network: To generate the missing regions guided with the HOG features in the first stage.

Most known deep learning-based systems algorithms have been summarized in Table 2, showing the inpainting technique used and evaluation for its' obtained results and used loss functions along with an evaluation for the algorithms perfromance.

Table 2 – Some deep learning image inpainting techniques.

Paper Title	Input Image	Loss Function	Merits	Demerits
D Pathak et al (2016), Context Encoders: Feature learning by inpainting	GT image, a binary mask	L2+ adv	• Doesn't require high memory usage • Simple • Performs well for center square missing regions	• Fails if the location of the missing region changed • Does not support random missing regions
C Yang et al (2016), High-resolution image inpainting using multi-scale neural patch synthesis	GT image, a binary mask	L2 + texture + TV	• Performs well for center missing region	• Slow algorithm • Does not support random missing regions • Fails when the image is not center symmetric images
S Iizuka et al (2017), Globally and Locally Consistent Image Completion	GT image, a binary mask	L2+ adv	• Performs well • Efficient	• Does not support random missing regions • Unable to handle complex structures
RA Yeh et al (2016), Semantic image inpainting with deep generative models	Face GT image, a binary mask	L1+adv	• Works well for simple structures	• Does not support random missing regions • Added Artifacts

Y Li et al (2017), Generative face completion	Face GT image, a binary mask	L2+ adv + segmentation	• Efficient • Restore textures	• Does not support random missing regions
P Isola et al (2016), Image-to-Image Translation with Conditional Adversarial Networks	GT image and binary mask	L1+adv	• Efficient • Performs well from random missing regions	• Does not support random missing regions
U Demir et al (2018), Image-to-Image Translation with Conditional Adversarial Networks	GT image and binary mask	L1+adv	• Efficient • Restore textures • Color distribution analysis	• Does not support high-resolution images
U Demir et al (2018), Patch-Based Image Inpainting with Generative Adversarial Networks	GT image and binary mask	L2+ adv	• Efficient • Performs well for center square missing regions	• Added artifacts • Fails in the case of images with different textures and colors
SM Uddin et al (2020), Global and Local Attention-Based Free-Form Image Inpainting	GT image and binary mask	L2 +adv	• Efficient • Performs well for random missing regions	• Does not support high-resolution images • Require high computational complexity and memory usage
J Yu et al (2018), Generative image inpainting with contextual attention	GT image and binary mask	Contextual loss+ Adv	• Performs well for fixed square missing region • Supports high-resolution images	• Does not support random shaped missing region
K Nazeri et al (2019), Edgeconnect: Generative Image Inpainting with Adversarial Edge Learning	GT image and binary mask	L2+ Adv + Perceptual + Style	• Efficient • Performs well for random missing regions	• Fails to produce good results in case of highly textured images
NM Salem et al (2021), A Novel Face Inpainting Approach Based on Guided Deep Learning	GT image and binary mask	L2+ Adv + Perceptual + Style	• 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 high-resolution images

Discussion

Although many techniques have been presented to solve image inpainting. Video inpainting (Ouyang, Wang and Chen 2021) is still an open research problem. Video inpainting is the process to fill in missing regions of a given video sequence with contents that are both spatially and temporally coherent. The existing approaches cannot consistently produce visually pleasing inpainted videos with long-range consistency. The main research point is to how to find the best weights for each video sequence. This area needs further investigation.

Conclusion

Image inpainting is an essential task for computer vision applications, due to the need for data modification using images, different editing tools such as image quality enhancement, image restoration, and others. In this paper, a brief image inpainting review is performed. Different categories of approaches have been presented including traditional approaches and deep learning approaches. We presented various techniques in traditional and deep learning. We concluded that no method can inpaint all the types of distortion in images but using deep learning produce very promising results for each category of the analyzed cases. However, the problem of deep learning is the high computational complexity and high memory usage. Future research has to pay more attention to presenting algorithms with less complexity and be able to handle both simple and complex structures at the same time.

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