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Generative Adversarial Networks for Image Restoration: Revolutions, Challenges and Future Look

Zikeng Chen

School of Computer Science and Engineering, South China University of Technology, Guangzhou, China
czk910293827@outlook.com

Abstract. Image restoration techniques based on Generative Adversarial Networks (GAN) have powerful image generation capability. The strength offers a new way to solve image restoration problems that are hard for traditional methods. This paper reviews the theory and research progress in this field. According to the type of image damage, the restoration tasks are divided into two categories: content loss and quality degradation. Correspondingly, restoration paths are summarized into the two directions of image complementation and image deblurring. In terms of image completion, the paper focuses on analyzing GAN methods based on conditional guidance and latent encoding. Their working mechanisms and suitable scenarios are discussed. For image deblurring, the essential differences between dynamic blurring and static blurring are explained. Targeted restoration strategies for each type are elucidated. The paper provides an in-depth analysis of representative models under each application direction. Their technical contributions and application scope are summarized. Finally, the core advantages of GANs in image restoration and current challenges are outlined. The paper concludes with an outlook on future development prospects.

Keywords: Image Restoration, Generative Adversarial Network, Image Inpainting, Image Deblurring

1. Introduction

In the field of image processing, image quality directly impacts its practical application value. In reality, images often suffer from missing information or contamination due to shooting angles, occlusions, or resolution limitations, making them unsuitable for many applications. With the advancement of computer vision technology, image restoration techniques have gained increasing importance. Their goal is to reconstruct and recover missing or contaminated areas based on known pixel information, finding widespread use in scenarios such as vintage photo restoration, evidence reconstruction, and watermark removal.

Traditional image restoration methods primarily fall into two categories: diffusion-based and patch-based. The former fills small-scale defects by propagating texture, while the latter repairs by replicating pixel blocks. However, both approaches have significant limitations: diffusion methods are only suitable for small-scale defects, and patch-based methods are computationally expensive,

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prone to failure, and lack an understanding of the image's overall semantic context, resulting in limited restoration effectiveness. For deblurring, traditional approaches rely on known blur kernels or parameter modeling. However, blur kernels are often unknown in practical applications, and non-end-to-end processing frequently leads to image distortion.

With advances in deep learning, generative models have introduced novel approaches to image restoration. Among these, Generative Adversarial Networks (GANs) demonstrate remarkable potential for recovering damaged images due to their powerful learning capabilities and unique advantages, significantly propelling the development of image restoration technology. This paper systematically reviews two major categories of GAN-based image restoration methods developed in recent years, analyzes their characteristics and advantages/disadvantages, and outlines future research directions based on the framework and principles of GANs and their derivative models.

2. Working principles of Generative Adversarial Networks and their variants

Since their introduction in 2014, Generative Adversarial Networks (GANs) have become a core method in fields such as image restoration. Their fundamental framework achieves joint optimization through adversarial training between a generator and a discriminator, as illustrated in Figure 1. The generator is tasked with producing realistic samples to deceive the discriminator, while the discriminator strives to accurately distinguish between genuine and synthetic samples. However, GAN training suffers from poor stability, susceptibility to pattern collapse leading to insufficient sample diversity, and difficulties in precisely controlling the generation process.

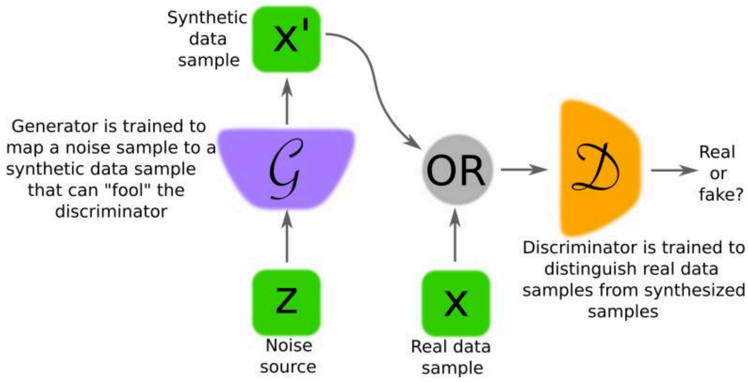

Figure 1. Basic framework of Generative Adversarial Networks

To overcome these limitations, researchers have proposed various improved models. The following is a brief overview of commonly used models.

Deep Convolutional Generative Adversarial Networks (DCGANs) incorporate convolutional neural network systems into GANs. They use techniques like fully convolutional structures, batch normalization, and Leaky ReLU. These improvements significantly enhance both image quality and training stability.

Conditional Generative Adversarial Networks (CGANs) introduce conditional information like category labels. This allows directed control over generated content. In tasks such as image restoration, CGANs effectively improve controllability.

Wasserstein Generative Adversarial Networks (WGANs) employ the Wasserstein distance as a loss metric, combined with regularization methods like weight clipping. This changes significantly

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mitigates mode collapse and gradient vanishing. Consequently, WGANs greatly improves training convergence and stability.

These improved models enhance GAN performance and applicability from different perspectives, such as advancements in network architecture, conditional control, and loss functions. They together promoted technological progress in image restoration and related fields.

3. Principles and applications of GANs in image restoration

Image restoration techniques based on Generative Adversarial Networks (GANs) use the powerful generative capabilities of GANs to reconstruct complete visual content from damaged images. Based on differences in restoration mechanisms, these techniques can be divided into two main types: The first type is image generation-based restoration. These methods reconstruct missing regions creatively through conditional guidance or latent space manipulation. Another type is image translation-based restoration. These methods directly input images through end-to-end networks, finding widespread application in tasks like image deblurring. In the following section, this paper reviews image restoration solutions based on GANs across two distinct application domains.

3.1. Image inpainting

Image inpainting techniques aim to restore missing regions in images. Traditional methods are limited to handling local regular occlusions and often suffer from issues like abrupt boundaries and texture discontinuities. With the advancement of deep learning and generative adversarial networks (GANs), modern approaches significantly enhance the realism and naturalness of inpainting results by deeply mining image texture, color, and semantic features. Currently, GAN-based approaches can effectively handle both regular and random occlusions, demonstrating increasingly robust adaptability and generalization capabilities.

3.1.1. Condition-guided image completion

To address the loss of detail in low-light images, Li et al. proposed a single-stage generative adversarial restoration model based on WGAN-GP, as shown in Figure 2 [1]. This method employs an encoder-decoder architecture combined with a multi-scale feature fusion module and introduces a dual-branch discriminator, significantly enhancing image visual realism and color consistency.

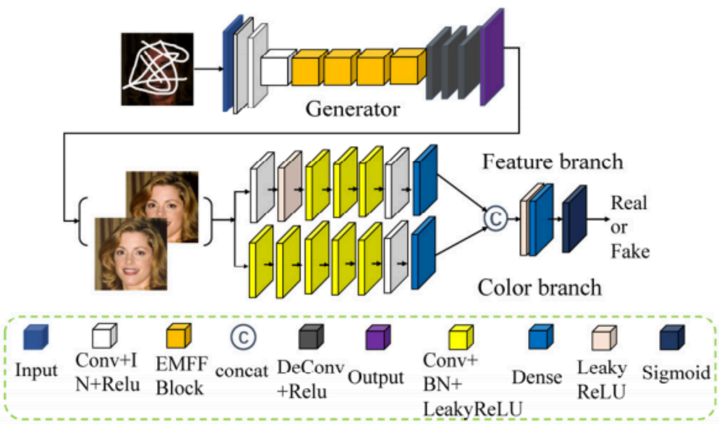

Figure 2. A single-stage generative adversarial restoration model based on WGAN-GP

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To address distortion and boundary discontinuity issues in panoramic images, Xu et al. proposed a cascaded generative adversarial network [2]. This method establishes a completion framework for irregularly shaped images through projection transformations, multi-scale feature extraction, and a dual discriminator design of PatchGAN, combined with distortion-aware networks and spectral normalization techniques. It provides a significant approach for resolving similar challenges.

3.1.2. Image completion based on latent coding

Latent encoding-based image completion methods work by mapping images to a low-dimensional latent space.Through manipulating their encodings, these approaches generate semantically reasonable and detail-rich content for missing regions.

The Deep Generative Model (DGM) proposed by Yeh et al. represents early pioneering work [3]. This method pre-trains a DCGAN. It then searches for the encoding z* that best matches the damaged image in the latent space. This code is fed into the generator to produce the restoration result. DGM demonstrates potential for addressing large-scale semantic loss. Nonetheless, limited by DCGANs's gradient vanishing issue, the results often sufferd from low-resolution restorations with noticeable noise.

Building on DGM, subsequent research has advanced in two directions: optimizing training stability and targeting specific structures. Chen et al. proposed a VAE-GAN hybrid model for repairing drone images [4]. This approach uses an encoder to extract deep features. A shared decoder and generator then perform reconstruction, with the training process illustrated in Figure 3. The introduced self-attention mechanism enhances the ability to preserve both local parts and global geometry. However, performance still degrades under extreme occlusion, limiting its generalization capabilities.

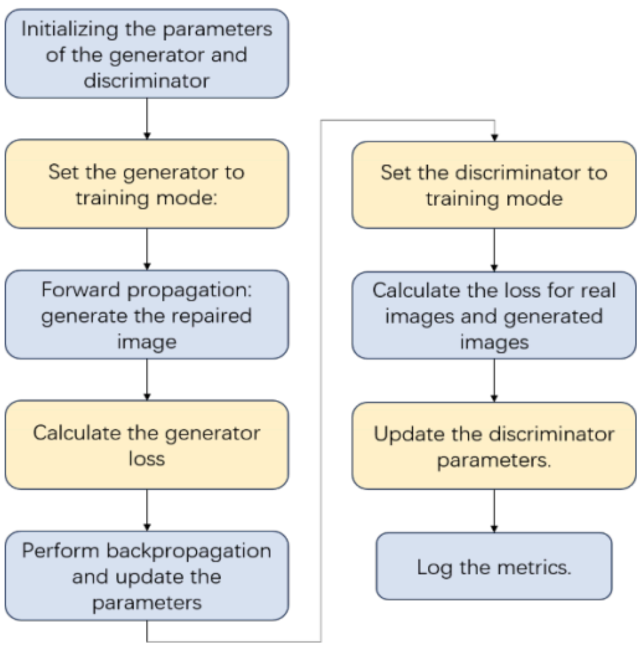

Figure 3. VAE-GAN model training flowchart

To improve fidelity and overcome early limitations, recent studies have turned to more powerful generative priors. For example, Xian et al. developed a method centered on StyleGAN2. They innovatively introduced a latent encoding w derived from a mapping network [5]. This encoding is

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concatenated with visible regions to form a global style embedding vector s, which modulates all layers of the generator. This style modulation mechanism generates high-resolution images rich in detail and stylistically consistent. It performs particularly well in handling large missing areas in complex scenes.

Despite significant progress in latent coding-based methods, they collectively face several challenges: model structures are often complex, training relies on large-scale data with high computational costs, and manipulating and interpreting latent spaces remains an open research topic.

3.1.3. Summary

Since the introduction of generative adversarial networks (GANs) and their application in image completion, both conditionally guided and latent-based completion approaches have been explored almost simultaneously. A systematic review of GAN-based image completion methods is summarized in Table 1. This section focuses on summarizing and organizing methods that leverage the GAN framework, annotating them according to different methodological classifications as well as their respective contributions and limitations.

Table 1. Summary of GAN-based image deblurring methods

Author	Year	Classification	Contribution	Limitations
Yeh et al.	2017	Image-based Restoration Methods / Latent Encoding-based Completion Methods	The proposed deep generative model addresses the challenge of completing large-area occlusions	Issues such as low resolution and gradient vanishing exist.
Li et al.	2023	Image-Based Restoration Method / Conditionally Guided Completion Method	A multi-scale feature fusion module has been designed, demonstrating outstanding performance in restoring details in low-light images.	Not validated on real low-light datasets; low-light conditions simulated solely through gamma correction.
Xu et al.	2024	Image-Based Restoration Method / Conditionally Guided Completion Method	We propose a cascaded generative adversarial network that effectively addresses distortion and boundary discontinuity issues in panoramic images.	The model is complex and training costs are high.
Chen et al.	2024	Image-based Restoration Methods / Latent Encoding-based Completion Methods	A hybrid model integrating VAE and GAN restores local details while maintaining consistency.	Repair results for extreme occlusions or complex backgrounds remain suboptimal, potentially resulting in localized inconsistencies.
Xian et al.	2025	Image-Based Restoration Method / Conditionally Guided Completion Method	Proposing a hybrid encoding + mask modulation architecture to simultaneously enhance global consistency, local detail, and generative diversity.	The computational complexity may be relatively high.

In the real world, image blurring arises from diverse causes. Broadly categorized, the primary types include: static blur, contrasting with motion blur, arises from factors like atmospheric scattering or improper focus due to depth of field. The characteristics of blur vary depending on its cause, necessitating tailored deblurring solutions based on GANs.

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3.2. Image De-blurring

3.2.1. Motion blur

Kunal et al.'s pioneering DeblurGAN constructs image deblurring as a supervised image translation task [6]. It employs a conditional GAN framework, taking blurred images as conditional inputs. A ResNet generator with global skip connections outputs sharp images, while WGAN-GP enhances training stability. The method integrates perceptual loss and adversarial loss to guide training, as illustrated in Figure 4. While demonstrating significant advantages in detail restoration, this method suffers from limitations such as incomplete global repair and suboptimal performance at high resolutions.

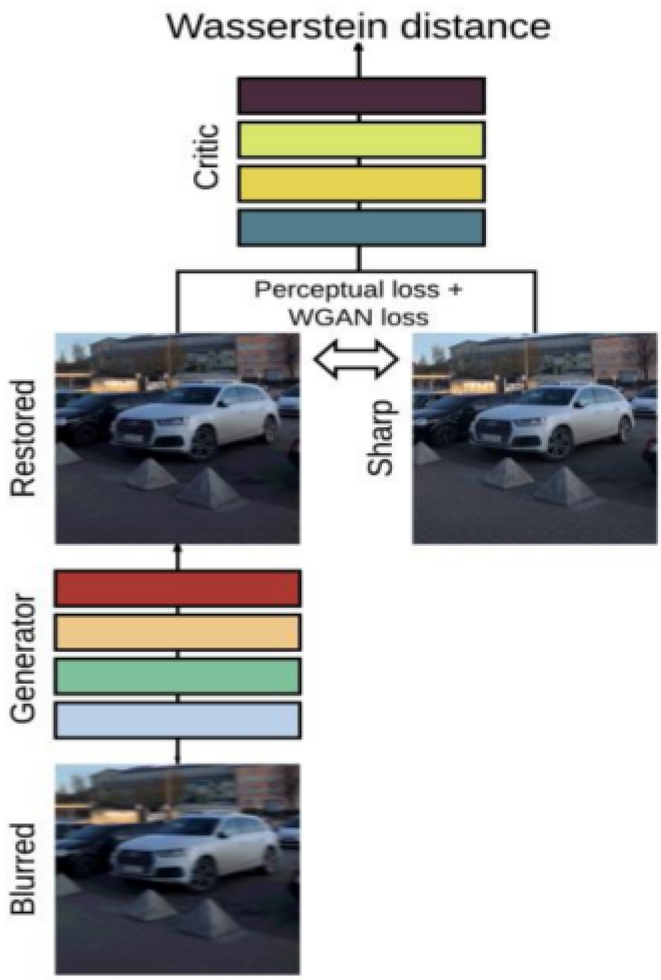

Figure 4. Training of DeblurGAN

Based on this foundation, Su et al. specifically improved the conditional GAN framework to address motion blur issues in terminal guidance of spinning projectiles. The generator employs an encoder-decoder structure to learn residual mappings. The discriminator introduces LSGAN loss to enhance training stability [7]. A multi-task composite loss function was constructed, comprising pixel loss, adversarial loss, gradient loss, and total variation loss. In specific scenarios, this approach achieved better results than DeblurGAN. However, its generalization capabilities remains limited due to excessive reliance on simulated data.

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To overcome the limitations of paired data, Wu et al. extended their research into the realm of unsupervised domain [8]. Their method is built upon CycleGAN. It constructs a bidirectional generation pathway, enabling learning from unpaired data through “fuzzy-clear” and “clear-fuzzy” cyclic mappings. The model is jointly optimized using the Wasserstein distance, gradient penalty, and perceptual loss. Their work provids a solution for real-world scenarios. However, the restoration capability under extremely fuzzy conditions still requires further improvement.

3.2.2. Static blur

Static blurring, a common issue in image degradation, arises from complex and diverse causes. Fundamental restoration problems typically focus on out-of-focus and haze degradation. Xuan et al. addressed focusing errors by proposing the GAN-based GovRGAN algorithm, which employs a pre-trained U-Net as the generator core and utilizes an encoder-decoder structure to learn deep features [9]. Turning to dehazing challenges, Zhong et al. addressed limitations of traditional methods—such as reliance on paired data and poor model generalization—by proposing an unsupervised image dehazing algorithm based on the CycleGAN framework [10]. Within this architecture, they enhanced the network's feature learning capabilities and training stability through optimized generator structures.

In professional applications, Li et al. proposed a gradient-information-guided generative adversarial network (GAN) for sunspot images affected by atmospheric turbulence [11]. Utilizing a feature pyramid network (FPN) as the generator, they enhanced semantic fusion through multi-scale feature extraction. During decoding, a gradient branch is constructed to jointly restore image content and gradient information. Dual discriminators constrain the authenticity of generated images and gradient maps, respectively. DeblurGANv2-Mobile is employed for preprocessing to enhance gradient guidance.

Underwater images often exhibit degradation due to the effects of water on light. Guo et al. proposed a multi-stage optimization framework based on an improved DCGAN to address color distortion and detail blurring caused by optical attenuation in underwater images [12]. Its network architecture is shown in Figure 5. This method employs a preprocessing module (MSD) to separate blurred regions from sharp features. It incorporates a Channel-Spatial Collaborative Attention (SCSA) module to dynamically correct color shifts and enhance textures. Additionally, it utilizes a dynamic course-weighting strategy to adaptively adjust multi-loss weights, thereby improving training stability and generating higher-quality images.

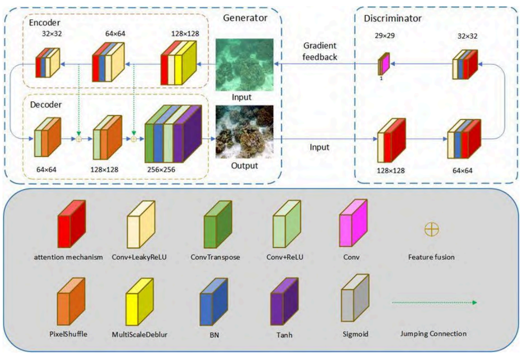

Figure 5. Improved model network structure

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3.2.3. Summary

In introducing generative adversarial networks to the field of image deblurring, researchers have adopted the concept of image translation to convert blurred images into clear ones. This progress has evolved through three main stages: supervised, self-supervised methods and unsupervised techniques.Afforts have also been made to advance deblurring methods from addressing general problems to tackling specialized ones. This section focuses on the restoration of blurred images. It summarizes and organizes methods that utilize generative adversarial networks. These approaches are annotated based on their respective contributions and limitations, ultimately presented in Table 2.

Table 2. Summary of GAN-based image deblurring methods

Author	Year	Classification	Contribution	Limitations
Wu et al.	2020	Image Translation-Based Restoration Method /Removal of Motion Blur	Superior deblurring performance compared to traditional CycleGAN on blurred text images in real-world scenarios	Model training takes a long time and incurs high computational costs.
Li et al.	2021	Image Translation-Based Restoration Method /Removal of Static Blur	A generator architecture integrating FPN with gradient branching is proposed to extract effective gradient information during the decoder phase, thereby enhancing the recovery of high-frequency details.	Model performance is highly dependent on the preprocessing stage.
Zhong et al.	2022	Image Translation-Based Restoration Method /Removal of Static Blur	Proposing an unsupervised defogging algorithm based on CycleGAN	Color distortion and color casts still occur in localized areas.
Kunal et al.	2024	Image Translation-Based Restoration Method/Removal of Motion Blur	Proposing an end-to-end motion blur restoration method based on WGAN-GP (DeblurGAN) that can handle images of arbitrary sizes.	Dependent on paired fuzzy-clear data sets
Su et al.	2024	Image Translation-Based Restoration Method /Removal of Motion Blur	Introducing a multi-loss function enhances defocusing effects and image smoothness.	The model exhibits limited generalization capabilities on non-training images.
Xuan et al.	2025	Image Translation-Based Restoration Method /Removal of Static Blur	Proposing the GovRGAN Restoration Algorithm Specifically Tailored for Government Data	Model training takes a long time and incurs high computational costs.
Guo et al.	2025	Image Translation-Based Restoration Method / Removal of Static Blur	The introduction of a channel-space collaborative attention mechanism enables dynamic calibration of color bias while enhancing texture details.	The model may exhibit unnatural color transitions or incomplete reconstruction of local details in certain extreme scenarios.

4. Conclusion

GANs demonstrate significant advantages in image restoration due to their powerful generative capabilities. Their flexible architecture facilitates the construction of multi-stage, multi-scale restoration frameworks. However, existing research still faces the following common challenges:

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First, limited model generalization capabilities, with most methods designed for specific scenarios and insufficient adaptability to complex backgrounds; Second, training stability and efficiency issues are prominent, coupled with high computational costs for complex models. Third, there is heavy reliance on paired data—for example, supervised methods require “damaged-intact” image pairs, which are difficult to obtain in real-world scenarios. Fourth, evaluation systems suffer from inconsistencies between subjective and objective metrics, making it challenging to comprehensively assess restoration quality.

Building upon current research achievements and shortcomings, future GAN-based image restoration studies can focus on the following directions: Firstly, to develop a unified multi-task restoration framework. Real-world image degradation often involves multiple types of damage. Future models should aim to handle diverse degradation types within a single architecture. Enhancing cross-modal and semantic understanding is equally important. Integrating multimodal cues—such as text, edges, and structural maps—can provide richer context. Tools like knowledge graphs and vision-language models may further improve high-level semantic reasoning. These approaches could help generate more semantically coherent and contextually consistent results. Additionally, advancing unsupervised and weakly supervised methods remains a priority. It can help models reduce dependency on paired training data, improving the model's generalization capabilities in real-world scenarios. Refining training strategies and evaluation systems cannot be neglected. Future work should aim to align objective metrics with human visual perception.

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