International Journal of Research in Engineering and Science (IJRES)
ISSN (Online): 2320-9364, ISSN (Print): 2320-9356
www.ijres.org Volume 12 Issue 12 ǁ December 2024 ǁ PP. 124-128

The Cross-Domain Application Research of a Super-Resolution Semantic Artifact Rectification Method

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Abstract
Generative Adversarial Networks (GANs) have shown promise in image generation tasks, but the artifacts they produce—such as unnatural textures, color distortions, and blurred edges—significantly affect the quality and usability of generated images. These artifacts are prevalent not only in image super-resolution but also in other image generation tasks, including image deraining, where the removal of rain interference is challenging. This paper presents a novel method for artifact localization and optimization in GAN-generated images, specifically extending artifact detection from super-resolution to image deraining. The approach consists of two main stages: artifact localization, where a model trained on the GAN-super-resolution dataset detects artifact regions, and artifact optimization, where a multi-model fusion strategy is used to enhance image quality by reducing artifacts. Extensive experiments across multiple deraining datasets demonstrate that our method improves image quality by reducing artifacts, preserving fine details, and enhancing visual fidelity. The results show that our method outperforms baseline deraining models in terms of PSNR, SSIM, and LPIPS, making it highly effective for real-world applications.
Keywords: *Image deraining, Generative Adversarial Networks (GANs), Artifact Rectification*

Date of Submission: 02-12-2024 Date of acceptance: 11-12-2024

I. INTRODUCTION

With the widespread application of Generative Adversarial Networks (GANs) [1]in the field of image generation, an increasing body of research has demonstrated that artifacts inevitably occur in GAN-generated images.[2,3]These artifacts are not only evident in the domain of image super-resolution (SR), but are also prevalent in other image generation tasks. Artifacts typically manifest as unnatural textures, color distortions, and blurred edges, phenomena that deviate from the characteristics of real-world images. These imperfections not only degrade the visual quality of the generated images but also negatively impact subsequent image analysis and processing tasks. Consequently, the detection and optimization of artifacts have become critical challenges in the field of image generation.

Figure 1: Artifact Issues in Image Generation Tasks

In the super-resolution task, GAN models significantly enhance image detail and clarity by reconstructing high-quality images from low-resolution inputs. However, due to the inherent instability in GAN training, artifact issues have become more pronounced, particularly during the restoration of high-frequency details. In these cases, generated images often suffer from excessive smoothing or local anomalies, leading to the loss or distortion of fine details. As discussed in DeSRA[4], artifact detection and optimization techniques play a vital role in the generation and restoration of super-resolution images.

However, artifact issues are not limited to the realm of image super-resolution. Numerous other image generation tasks, such as image deraining, image defogging, and image synthesis, also face challenges with artifacts. In the image deraining task, GAN-generated images may exhibit blurred background details or overly smooth effects, compromising the reconstruction of details post-rain removal. In image defogging, generated images may suffer from color and contrast deviations, preventing the faithful restoration of the natural appearance of the image. In image synthesis, artifacts often manifest as unnatural textures or structures, which can lead to incoherent generated content or failure to align with real-world scene characteristics.

We have trained a deep learning model on the super-resolution artifact dataset (DeSRA) to locate artifact positions and optimize these artifacts by combining the results of different GAN models, with an aim to extend this approach to the image deraining task. While the manifestation of artifacts differs in deraining, their impact is essentially similar—affecting image quality and the reliability of the generation to varying degrees. To validate the generalization capability of our proposed method, we conducted extensive evaluations across multiple deraining datasets. Experimental results show that our proposed artifact correction strategy significantly improves the quality of generated images, enhances detail recovery accuracy, and effectively mitigates the impact of artifacts. Our method demonstrates strong cross-task adaptability when handling images with complex backgrounds and details.

Specifically, our method consists of two main steps: first, in the artifact localization phase, we trained a model using DeepLabV3+[5] on the GAN-SR artifact dataset to precisely locate artifact regions; second, in the artifact optimization phase, we employed a multi-model fusion strategy to compensate and repair the artifact regions by combining the results from different models, thereby improving image quality. Notably, in the image deraining task, the manifestation of artifacts differs from that in super-resolution, requiring the artifact localization and optimization methods to exhibit greater adaptability and flexibility. To comprehensively assess the scalability of our approach, we validated it on multiple deraining task datasets.

Our main contributions can be summarized in two key points:

Extension of the Super-Resolution Artifact Problem to Image Deraining: We are the first to extend the artifact detection and optimization problem, which has been primarily studied in the context of super-resolution, to the image deraining domain. This expansion involves adapting the techniques developed for handling artifacts in super-resolved images to tackle the specific challenges presented by derained images, which often exhibit different types of artifacts. This contribution not only highlights the relevance of artifact management in various image generation tasks but also opens new avenues for applying super-resolution-based solutions to other image enhancement areas.

Demonstrated Effectiveness Across Multiple Deraining Datasets: Our method shows strong performance in deraining tasks, as demonstrated by extensive experiments on multiple deraining datasets. After optimization, all methods we evaluated outperform the baseline approaches, leading to significant improvements in image quality. This enhancement is particularly evident in terms of artifact reduction, detail preservation, and overall visual fidelity. The results underscore the effectiveness and adaptability of our proposed approach, showing its potential to generalize across various deraining tasks and datasets.

II. METHOD

2.1 Image Deraining Task

Image deraining is a crucial task in the field of image restoration, aiming to remove the visual effects of rain streaks from images and restore the underlying scene's details[6]. Rainfall, particularly in outdoor scenes, significantly degrades image quality by introducing rain streaks, which obscure important scene information. These rain streaks can be difficult to remove due to their varying shapes, sizes, and intensities, as well as the interaction with other visual elements in the scene.

In the context of image deraining, the goal is to recover a rain-free version of the input image while preserving its sharpness and natural details. The process typically involves two key challenges: (1) identifying and isolating rain streaks from the background, and (2) reconstructing the missing image information from the rain-affected regions.

Mathematically, the image deraining task can be represented as the decomposition of the observed rainy image into two components:

$$I = R + B \tag{1}$$

Where: I is the input rainy image. R is the rain streaks that need to be removed. B is the background (the desired clean image).

The objective is to estimate the background image B from the observed rainy image I by effectively removing R, which represents the rain interference. Additionally, the model must account for the intricate interactions between the rain streaks and the underlying scene, necessitating a delicate balance between rain removal and the preservation of fine details such as textures, edges, and object boundaries. The task becomes even more difficult when the rain streaks overlap with critical features of the scene, making it harder to distinguish between the noise introduced by the rain and the true image content.

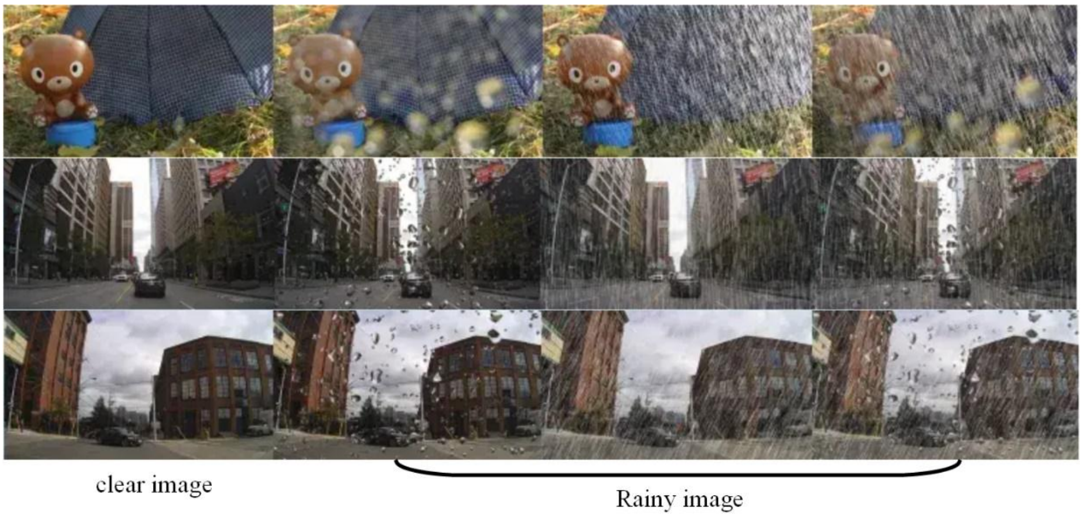

Figure 2: Image Deraining Task

Recent advancements in deep learning, particularly Generative Adversarial Networks (GANs), have shown promise in addressing the image deraining problem. GAN-based approaches attempt to model the distribution of clean images and rain patterns, enabling the generation of high-quality rain-free images that maintain the natural characteristics of the scene. However, these models are still susceptible to generating artifacts in certain cases, especially in challenging scenarios where the rain patterns are dense or irregular. Therefore, effective artifact detection and optimization techniques are crucial for improving the performance of image deraining models.

2.2 Artifact Rectification Method

Image deraining, which aims to remove rain interference from rainy images, is a challenging task due to the complex spatial structures of rain streaks and the need for fine detail recovery of the underlying scene. In this paper, we propose a novel method for artifact localization and optimization, designed to effectively address these challenges. Our approach consists of two key stages: artifact localization and artifact optimization. In the localization stage, a model is used to accurately identify the rain interference regions. In the optimization stage, the identified artifact regions are processed using a combination of classic GAN-based deraining models, allowing for enhanced deraining performance by mitigating the negative impact of artifacts. This dual-stage process ensures that the generated rain-free image maintains high quality while minimizing the artifacts that often arise during the deraining process.

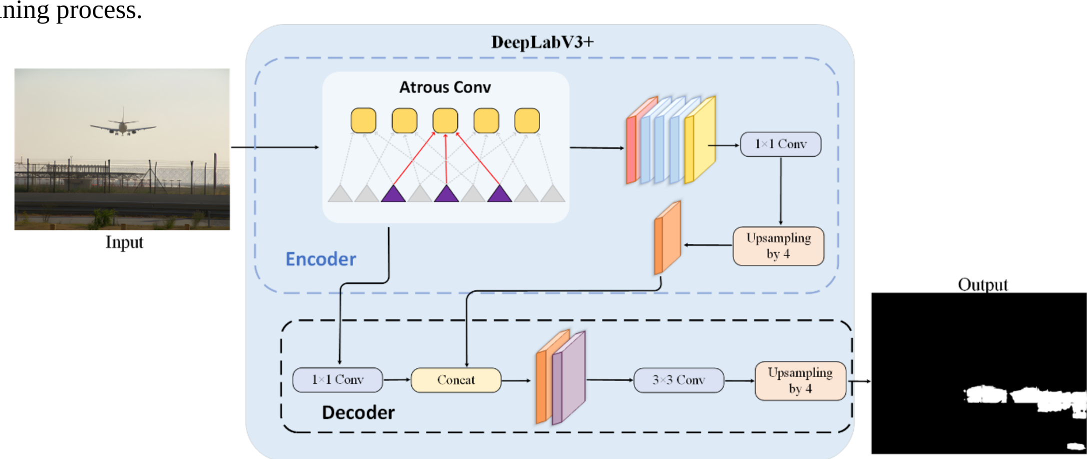

Figure 3: Artifact Localization Model

Artifact Localization: As shown in Figure 3, the artifact localization model is trained using the GAN-SR artifact dataset introduced in DeSRA. This model, based on DeepLabV3+, is specifically designed to accurately locate artifact regions in the rainy image. By applying this model to the image deraining task, we can effectively pinpoint areas affected by rain interference, such as raindrops and rain streaks. Once these regions are identified, they can be processed in the subsequent optimization phase to reduce their impact on the final image quality.

Artifact Optimization: During the artifact optimization phase, we incorporate three well-established image deraining GAN models: DerainCycleGAN[7], VRGNet[8], and Semi-DerainGAN[9]. Each of these models has its own strengths in dealing with different aspects of rain removal, and their outputs are combined to improve the overall performance of the deraining process.

DerainCycleGAN: Built on the CycleGAN framework, DerainCycleGAN introduces a rain-specific loss function, enabling the model to perform image deraining under an unsupervised learning paradigm. The adversarial training between the generator and discriminator allows DerainCycleGAN to effectively remove rain interference while preserving the image structure.

VRGNet: VRGNet is a data-driven model that implicitly learns the general statistical distribution of rain patterns. By leveraging the learned generator, the model is capable of generating rain patches that simulate various training conditions, which helps enhance and diversify the dataset used for training. This aids in improving the robustness of the model.

Semi-DerainGAN: This model incorporates a semi-supervised learning approach, utilizing both rainy and clean image pairs for training. This strategy optimizes the deraining effect by better recovering fine details from the rain-free image while simultaneously eliminating rain interference.

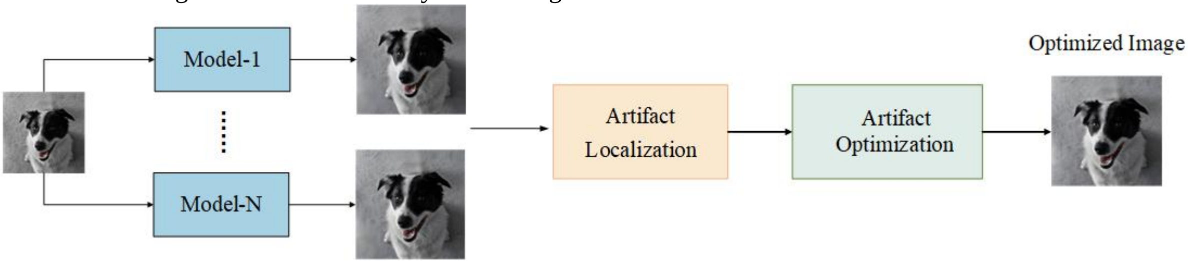

Figure 4: Framework Overview

The outputs from these three models are processed through the artifact localization model to identify the regions affected by rain interference. For the non-artifact regions, a fusion-based optimization strategy is employed to complement and enhance the deraining results. This multi-model approach ensures that the image deraining process is highly effective in both eliminating rain interference and preserving image details. The detailed workflow is illustrated in Figure 4, with artifact localization serving as the critical foundation for subsequent optimization. By leveraging this dual-stage method, we significantly improve the quality of derained images, demonstrating the effectiveness of our approach.

III. EXPERIMENTS

We conducted experiments using several publicly available image deraining datasets, including classic datasets such as Rain100L and Rain12, as well as newer real-world deraining datasets like SPA-Data. These datasets encompass a wide range of rain intensities and types, allowing for a comprehensive evaluation of the performance of different methods across various scenarios. The experimental results are summarized in Table 1.

Table 1 Deraining Task Experimental Results

DataSet	Rain100L	Rain12	Rain800	SPA-Data
Metrics	PSNR/SSIM/LPIPS	PSNR/SSIM/LPIPS	PSNR/SSIM/LPIPS	PSNR/SSIM/LPIPS
DSC[10]	27.34/0.849/0.0923	30.07/0.866/0.1012	18.56/0.600/0.1798	34.95/0.942/0.0784
GMM[11]	29.05/0.872/0.0911	32.14/0.916/0.0877	20.46/0.730/0.1465	34.30/0.943/0.0806
DDN[12]	32.38/0.926/0.0720	34.04/0.933/0.0715	20.88/0.762/0.1239	35.02/0.940/0.0761
DerainCycleGAN[7]	31.49/0.936/0.0734	34.44/0.952/0.0703	24.32/0.842/0.1183	34.12/0.950/0.0718
VRGNet[8]	35.56/**0.966**/0.0630	35.28/0.957/0.0662	24.91/0.884/0.0854	35.76/0.961/0.0523
SemiDerainGAN[9]	34.12/0.958/0.0632	35.86/0.960/0.0679	25.29/0.868/0.0815	35.47/0.956/0.0594
CycleGAN+Ours	34.03/0.951/0.0606	35.37/0.955/0.0634	25.16/0.853/0.0799	34.86/0.943/0.0680
VRGNet+Ours	**35.99**/0.965/**0.0556**	35.44/0.952/0.0653	25.20/**0.889**/0.0717	**35.92**/**0.965**/0.0510

Semi-Derain+Ours	34.52/0.962/0.0613	**36.02**/**0.963**/**0.0601**	**25.31**/0.870/**0.0649**	35.60/0.951/**0.0502**

From the comparison between our method and DerainCycleGAN, VRGNet, Semi-DerainGAN, and previous methods in terms of PSNR, SSIM, and LPIPS, it is evident that the multi-model fusion approach with artifact optimization outperforms the single-model results on most metrics. Notably, our method shows significant superiority in terms of LPIPS. The optimized images exhibit a substantial improvement in overall visual quality, effectively merging the advantages of multiple models.

Our method identifies and eliminates residual rain streaks, which are treated as artifacts, while preserving the fine details of the underlying scene. Through SSIM, it is clear that our approach successfully retains the structural integrity of the image, avoiding any discontinuities or inconsistencies in the fused results. This indicates that our method not only improves visual quality but also preserves the structural fidelity of the images, making it highly effective for real-world applications.

In terms of specific performance, our approach demonstrated a considerable enhancement in both subjective and objective evaluation metrics. For example, in the SPA-Data dataset, our method achieved superior results with a PSNR of 35.92, SSIM of 0.965, and LPIPS of 0.0510, which shows that the optimized deraining process leads to high-quality images that are closer to ground truth. This result emphasizes the ability of our method to address challenges such as complex rain patterns and fine detail preservation in real-world scenarios.

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