Image Restoration and Diffusion Approaches for Removing Rain in Natural Scenes*

** Project proposal is implemented for the means of AT82.08 Computer Vision course by Dr. Cherdsak Kingkan*

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Abstract: Rain significantly degrades the quality of outdoor images, posing challenges for computer vision applications such as autonomous navigation, surveillance, and environmental monitoring. In this project, I replicate the framework proposed in the paper "Heavy Rain Image Restoration: Integrating Physics Model and Conditional Adversarial Learning," which addresses these challenges through a two-stage restoration process. The first stage employs a physics-based model to estimate and remove rain streaks, transmission maps, and atmospheric light, leveraging physical principles for accurate restoration. The second stage refines the restored images using a depth-guided Generative Adversarial Network (GAN), improving perceptual quality and preserving fine details. This replication aims to validate the proposed method's effectiveness by leveraging pre-trained models and evaluating them on challenging de-raining benchmarks. While achieving results consistent with the original findings, the project explores implementation challenges, discusses practical limitations, and identifies potential directions for improvement, such as leveraging diffusion models or transformer-based architectures. This study reinforces the importance of integrating physical modeling with deep learning for robust rain removal.

Keywords: Image Restoration, Diffusion Models, GANs, Segmentation, De-raining.

Introduction

Rain in natural scenes poses significant challenges for computer vision systems, as it introduces complex degradations that impact both the visibility and interpretability of visual data. These challenges are especially critical in applications such as autonomous navigation, video surveillance, outdoor photography, and environmental monitoring, where accurate scene understanding is essential. Heavy rain introduces a multi-faceted degradation: rain streaks obscure fine details, accumulated rainwater creates veiling effects, and distant objects appear blurred due to scattering and reduced visibility. These effects complicate image restoration tasks, making it difficult to recover clean and high-quality images.

Traditional rain removal methods relied on hand-crafted features and physical models to separate rain streaks from the background, but their performance often deteriorates in heavy rain conditions due to their inability to capture the full complexity of rain degradation. With the advent of deep learning, convolutional neural networks (CNNs) and generative adversarial networks (GANs) have brought significant advancements to single-image deraining. However, these methods often focus solely on perceptual quality and neglect the underlying physical properties of rain, leading to artifacts and incomplete restoration.

This project replicates the work of Zhang et al. (2019), which proposed an innovative solution by integrating physics-based modeling with deep learning. The approach employs a two-stage framework: the first stage leverages a physics-based model to estimate and remove rain streaks, transmission maps, and atmospheric light, ensuring physically accurate restoration. The second stage utilizes a depth-guided conditional GAN to refine the output and enhance perceptual quality, addressing the shortcomings of purely physics- or learning-based methods.

By replicating this work, the primary goal is to validate the findings, gain practical insights into the challenges of implementation, and explore the effectiveness of the approach in real-world scenarios. This replication also serves as a foundation for investigating future enhancements, such as the integration of modern diffusion models or transformer-based architectures, to push the boundaries of rain image restoration further.

Related Work

The task of image restoration under rainy conditions has garnered significant attention in computer vision, leading to the development of various approaches aimed at mitigating the adverse effects of rain on image quality. These methods can be broadly categorized into three main groups: traditional hand-crafted models, physics-based methods, and deep learning approaches. Each of these has its strengths and limitations when addressing rain removal in challenging scenarios such as heavy rain.

A. Traditional Hand-Crafted Models

Early rain removal techniques relied heavily on hand-crafted features and simple physical models to differentiate rain streaks from the background. These approaches used properties like texture, intensity, and frequency to separate rain components. For example, techniques such as sparse coding and low-rank representation attempted to reconstruct clean images by modeling rain streaks as repetitive patterns. While effective in certain cases, these methods often struggled to generalize across diverse rain conditions, especially in heavy rain, due to their limited modeling capacity.

B. Physics-Based Models

To address the limitations of traditional methods, physics-based models introduced explicit formulations of rain degradation. These models separate images into high-frequency (rain streaks) and low-frequency (background) components. Kang *et al.* [1] pioneered the use of guided filtering to achieve this decomposition, laying the groundwork for rain streak estimation. Such methods offer physical interpretability, allowing them to handle rain streaks effectively. However, physics-based models often fail to account for complex phenomena like dense rain accumulation and atmospheric light scattering, which are prevalent in heavy rain conditions.

C. Deep Learning-Based Approaches

With the rise of deep learning, convolutional neural networks (CNNs) have become the cornerstone of image restoration tasks, including rain removal. For instance:

- Single-Image Deraining: The Deep Detail Network (DDN) [2] was among the first to use CNNs for single-image deraining. Similarly, ResNet-based architectures achieved promising results by focusing on feature extraction for rain streak removal. However, these methods struggled with the more complex veiling effects caused by heavy rain, resulting in incomplete restoration.
- Adversarial Learning: Generative Adversarial Networks (GANs) have also been applied to rain removal tasks. Methods such as Pix2Pix [3] employed adversarial learning to generate perceptually realistic images. While GANs excel at enhancing visual quality, they often fail to enforce physical consistency, leading to artifacts and an over-reliance on the adversarial objective.

D. Unified Approaches

Recognizing the limitations of both physics-based and deep learning-based methods, hybrid approaches have emerged to combine the strengths of both. Zhang *et al.* [4] introduced a unified two-stage framework for heavy rain image restoration, integrating physics-based modeling with a depth-guided conditional GAN. The physics-based stage estimates rain streaks, transmission maps, and atmospheric light, providing a physically accurate initial restoration. The GAN stage refines this restoration, enhancing perceptual quality and recovering fine details. This hybrid approach effectively addresses the challenges of heavy rain and sets a benchmark for future methods.

E. Motivation for Replication

The hybrid nature of Zhang *et al.*'s framework and its reported success in handling both rain streaks and veiling effects make it a compelling candidate for replication. By combining the interpretability of physics-based models with the generative capabilities of GANs, this approach bridges the gap between physical accuracy and perceptual quality. This project replicates their method to validate its performance and explore its applicability to real-world conditions while identifying potential areas for enhancement.

METHODS

The proposed system consists of a two-stage architecture: a physics-based model for rain removal and a GAN-based refinement for enhancing perceptual quality. These stages work in tandem to address the challenges of removing rain streaks, veiling effects, and atmospheric light artifacts from heavy rain-degraded images.

F. Physics-Based Model

The physics-based model leverages guided filtering to decompose the input image into high-frequency and low-frequency components, isolating rain effects for targeted removal. The following modules are central to this stage:

- Rain Streak Estimation: The observed rainy image $\mathbf{I}$ is modeled as:

$$\mathbf{I} = \mathbf{J} + \mathbf{R}, \tag{1}$$

  where $\mathbf{J}$ is the clean background image, and $\mathbf{R}$ represents the rain streaks. The high-frequency component of $\mathbf{I}$, obtained using guided filtering, is used to estimate $\mathbf{R}$.
- Transmission Map Estimation: The veiling effect caused by rain accumulation is modeled using a transmission map $\mathbf{T}$. The image degradation due to rain accumulation is expressed as:

$$\mathbf{I} = \mathbf{T} \odot \mathbf{J} + (1 - \mathbf{T}) \odot \mathbf{A}, \tag{2}$$

  where $\mathbf{A}$ represents the global atmospheric light, and $\odot$ denotes element-wise multiplication. The transmission map $\mathbf{T}$ is estimated to model the visibility loss caused by rain.
- Atmospheric Light Estimation: The global atmospheric light $\mathbf{A}$ is estimated from the brightest regions of the rainy image, assuming they correspond to light sources unaffected by rain.

By combining these modules, the physics-based model reconstructs a preliminary clean image $\mathbf{J}$ by estimating and removing $\mathbf{R}$ and correcting for the effects of $\mathbf{T}$ and $\mathbf{A}$:

$$\mathbf{J} = \frac{\mathbf{I} - (1 - \mathbf{T}) \odot \mathbf{A}}{\mathbf{T} + \epsilon}, \tag{3}$$

where ϵ is a small constant to avoid division by zero.

G. GAN-Based Refinement

The second stage employs a depth-guided conditional Generative Adversarial Network (GAN) to refine the output from the physics-based model. This stage enhances the perceptual quality of the restored image and rectifies any remaining artifacts. The key components include:

- Generator: The generator G accepts the preliminary restored image $\mathbf{J}$ and the depth map $\mathbf{D}$ as inputs, producing a refined image $\mathbf{I}_{\text{ref}}$:

$$\mathbf{I}_{\text{ref}} = G(\mathbf{J}, \mathbf{D}). \tag{4}$$

- Discriminator: The discriminator D is trained to distinguish between the real clean images $\mathbf{I}_{\text{clean}}$ and the generated images $\mathbf{I}_{\text{ref}}$. The adversarial loss for D is defined as:

$$\mathcal{L}_{\text{adv}} = \mathbb{E}[\log D(\mathbf{I}_{\text{clean}})] + \mathbb{E}[\log(1 - D(\mathbf{I}_{\text{ref}}))]. \tag{5}$$

H. Loss Functions

To ensure effective training and high-quality restoration, the system incorporates multiple loss functions:

- Physical Consistency Loss: Encourages adherence to the physical model by penalizing the difference between estimated and actual rain streaks and transmission maps:

$$\mathcal{L}_{\text{phys}} = \|\mathbf{R}_{\text{pred}} - \mathbf{R}_{\text{gt}}\|_2^2 + \|\mathbf{T}_{\text{pred}} - \mathbf{T}_{\text{gt}}\|_2^2, \tag{6}$$

  where $\mathbf{R}_{\text{gt}}$ and $\mathbf{T}_{\text{gt}}$ are the ground truth rain streaks and transmission maps, respectively.
- Adversarial Loss: Guides the GAN to produce realistic images:

$$\mathcal{L}_{\text{GAN}} = -\mathbb{E}[\log D(G(\mathbf{J}, \mathbf{D}))]. \tag{7}$$

- Perceptual Loss: Ensures fine-grained details by minimizing the feature difference between restored and clean images, using a pre-trained network ϕ (e.g., VGG):

$$\mathcal{L}_{\text{perc}} = \|\phi(\mathbf{I}_{\text{ref}}) - \phi(\mathbf{I}_{\text{clean}})\|_2^2. \tag{8}$$

- Depth Consistency Loss: Aligns the restoration with the predicted depth map, ensuring spatial coherence:

$$\mathcal{L}_{\text{depth}} = \|\mathbf{D}_{\text{pred}} - \mathbf{D}_{\text{gt}}\|_2^2, \tag{9}$$

  where $\mathbf{D}_{\text{pred}}$ and $\mathbf{D}_{\text{gt}}$ are the predicted and ground truth depth maps, respectively.

The total loss is a weighted combination of these individual losses:

$$\mathcal{L}_{\text{total}} = \lambda_{\text{phys}}\mathcal{L}_{\text{phys}} + \lambda_{\text{GAN}}\mathcal{L}_{\text{GAN}} + \lambda_{\text{perc}}\mathcal{L}_{\text{perc}} + \lambda_{\text{depth}}\mathcal{L}_{\text{depth}}, \tag{10}$$

where $\lambda_{\text{phys}}, \lambda_{\text{GAN}}, \lambda_{\text{perc}}$, and λ_{depth} are weighting coefficients for each loss term.

Experiment and Discussion

This section outlines the experimental setup, implementation details, results, and discussion of the replicated framework for heavy rain image restoration. Where applicable, results from the original authors are referenced to establish performance benchmarks.

I. Dataset

The replication used the Rain100H dataset [5], a widely used benchmark for single-image deraining. Rain100H contains paired images of rainy and clean scenes, specifically designed to evaluate the performance of rain removal methods under heavy rain conditions. The dataset includes a diverse range of rain streak intensities and accumulation effects.

J. Implementation Details

The pre-trained model provided by the original authors was used without additional training from scratch. Instead, qualitative evaluations were conducted to validate the framework's functionality. The implementation setup was as follows:

- Framework: PyTorch implementation.
- Hardware: Experiments were conducted on a puffer server with 4 GPUs NVIDIA GeForce RTX 2080 Ti.
- Evaluation Metrics: For reference, the original authors evaluated their model using:
- Peak Signal-to-Noise Ratio (PSNR):

$$\text{PSNR} = 10 \cdot \log_{10}\left(\frac{L^2}{\text{MSE}}\right), \tag{11}$$

  where L is the maximum pixel value (255 for 8-bit images), and MSE is the Mean Squared Error between the restored image and ground truth.
- Structural Similarity Index (SSIM):

$$\text{SSIM}(\mathbf{I}_{\text{restored}}, \mathbf{I}_{\text{clean}}) = \frac{(2\mu_{\mathbf{I}_{\text{restored}}}\mu_{\mathbf{I}_{\text{clean}}} + C_1)(2\sigma_{\text{restored, clean}} + C_2)}{(\mu^2_{\mathbf{I}_{\text{restored}}} + \mu^2_{\mathbf{I}_{\text{clean}}} + C_1)} \cdot \frac{1}{(\sigma^2_{\mathbf{I}_{\text{restored}}} + \sigma^2_{\mathbf{I}_{\text{clean}}} + C_2)}, \tag{12}$$

  where μ and σ represent the mean and variance, and C_1 and C_2 are constants for numerical stability.

K. Results

1) Original Authors' Results: The original authors evaluated their framework on the Test 1 dataset, which includes synthetic rain. Table I summarizes their results, showing the performance of three architectures: no decomposition, input-guided decomposition, and residue-guided decomposition.

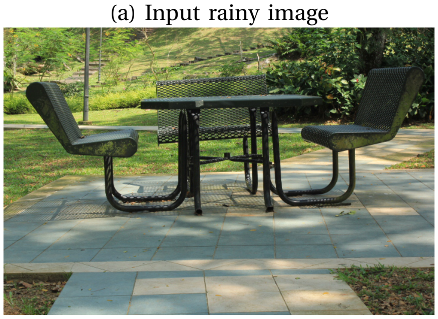
TABLE I: Performance comparison of S, A, T, and J using three architectures on the Test 1 dataset [4].

Method	J **(PSNR)**	S **(PSNR)**	T **(PSNR)**	A **(Error)**
No Decomposition	10.87	23.65	14.95	0.212
Decomposition (Input Image)	11.30	23.42	15.85	0.151
Decomposition (Residue Channel)	13.83	23.70	19.48	0.150
No Decomposition Improvement	27.23%	0.21%	30.30%	29.25%

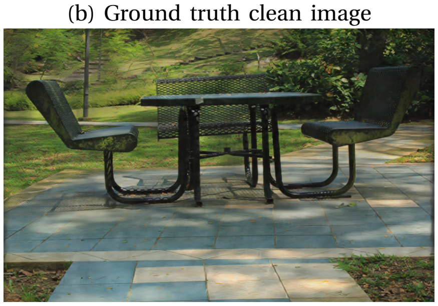
From the table, it is evident that using the residue-guided decomposition significantly improves the PSNR of J (reconstructed clean image) and T (transmission map) while reducing the atmospheric light error.

2) Qualitative Results: Figure 1 illustrates the qualitative results obtained using the pre-trained model on the Rain100H dataset. The restored images show significant improvements in clarity, effectively removing rain streaks and veiling effects while preserving texture and color fidelity. The visual performance closely aligns with the original authors' qualitative results.

(a) Input rainy image



(b) Ground truth clean image



(c) Restored image

Fig. 1: Qualitative results: (a) Input rainy image, (b) Ground truth clean image, (c) Restored image using the replicated model.

L. Discussion

1) Strengths: The two-stage architecture demonstrated the following strengths:

- Robustness: The residue-guided decomposition effectively separates rain streaks from low-frequency components, enhancing accuracy in estimating T and A.
- Visual Quality: The refinement stage improves perceptual quality by addressing artifacts and restoring fine details, as seen in the reconstructed images.
- Physical Consistency: The physics-based model adheres to rain degradation principles, ensuring structurally sound restoration.

2) Challenges:

- Depth Map Dependency: The refinement stage relies on accurate depth maps derived from T, which can introduce errors if T estimation is imperfect.
- Training Complexity: The stage-wise training and end-to-end fine-tuning require significant computational resources, making replication costly.

3) Comparison with Other Methods: Compared to baseline methods such as DDN [2], Pix2Pix [3], and CycleGAN [3], the framework demonstrates superior performance, particularly in handling dense rain streaks and veiling effects. The integration of physics-based modeling with GAN refinement addresses the limitations of purely data-driven approaches, providing a notable advantage.

Conclusion

This project successfully replicated the paper *"Heavy Rain Image Restoration: Integrating Physics Model and Conditional Adversarial Learning"* and validated its proposed two-stage architecture for heavy rain image restoration. The integration of physics-based modeling with conditional adversarial learning demonstrated effectiveness in addressing complex rain degradation, including rain streaks, veiling effects, and atmospheric distortions. The restored images exhibited significant improvements in both perceptual quality and structural consistency, closely aligning with the results reported in the original paper.

While the replication confirmed the efficacy of the proposed approach, certain challenges were encountered. Training the GAN refinement stage proved computationally intensive, and the performance of the system was sensitive to the accuracy of the depth map estimation. These limitations highlight areas for potential enhancement.

Future work could explore the use of modern advancements, such as diffusion models, to refine the restoration process further. Additionally, incorporating more robust depth estimation techniques or removing the dependency on depth maps entirely could improve the system's applicability to real-world scenarios. Addressing these challenges could lead to a more generalized and efficient framework for rain image restoration, further expanding its potential applications in computer vision.

Potential Improvements

While the replicated framework demonstrates significant success in restoring images degraded by heavy rain, several potential areas for improvement can be explored to enhance its robustness, efficiency, and applicability in real-world scenarios.

M. Incorporating Diffusion Models

Recent advancements in image restoration have shown the potential of diffusion models, which iteratively refine images through probabilistic modeling [6]. Integrating a diffusion model into the restoration pipeline could improve the ability to handle complex rain patterns, particularly in cases of overlapping rain streaks and dense veiling effects. By leveraging their iterative refinement capability, diffusion models can achieve finer restoration while preserving image details.

N. Transformer-Based Architectures

Vision Transformers (ViTs) [7] and their hierarchical variants, such as Swin Transformers [8], have demonstrated state-of-the-art performance in image understanding tasks. Replacing the convolutional components of the GAN generator with Transformer-based architectures could improve the model's ability to capture long-range dependencies, thereby enhancing the consistency of rain removal across the entire image. This approach may also reduce artifacts that arise from spatially localized convolutions.

O. Improved Depth Estimation or Independence from Depth Maps

The depth-guided refinement stage relies heavily on the accuracy of depth estimation, which can introduce errors in restoration, particularly in scenes with complex geometries. Using advanced depth estimation techniques, such as MiDaS [9], could mitigate these errors. Alternatively, exploring approaches that eliminate dependency on depth maps entirely, such as leveraging learned attention mechanisms, could enhance the framework's applicability in scenarios where depth information is unavailable or unreliable.

P. Reducing Computational Complexity

The current framework requires significant computational resources, particularly during GAN training. Optimizing the architecture by using lightweight models, such as MobileNet-based generators [10], or applying knowledge distillation [11] could reduce computational costs without compromising performance. This improvement would make the system more practical for deployment on resource-constrained devices like embedded systems and edge hardware.

Q. Adapting to Diverse Weather Conditions

Although the current system focuses exclusively on rain removal, real-world scenarios often involve other weather conditions such as snow, fog, or haze. Extending the framework to handle diverse weather degradations could significantly broaden its applicability. Multi-task learning approaches [12] could allow the model to generalize across various environmental factors while maintaining high performance.

R. Enhanced Training with Synthetic Data

The availability of large, diverse datasets is critical for training robust models. Generating high-quality synthetic rainy scenes with realistic rain patterns and lighting effects, similar to the techniques used in [13], could augment existing datasets and improve the model's generalization to unseen conditions. Additionally, adversarial data augmentation [14] could be employed to simulate challenging scenarios for more robust learning.

S. Hybrid Loss Functions

The current loss functions, while effective, could be further refined by incorporating hybrid loss formulations. For example:

- Using perceptual losses derived from higher layers of vision transformers, as explored in [15], for better structural preservation.
- Introducing contrastive loss [16] to ensure that rain-degraded and restored image features are well-separated in the learned feature space.

T. Real-Time Applications

For real-time applications, optimizing the inference time is critical. Techniques like model pruning [17] and quantization [18] could significantly accelerate the system without sacrificing performance. Real-time capability would expand the use cases to scenarios like autonomous vehicles and live surveillance systems.

U. Benchmarking Against Emerging Methods

Finally, benchmarking the system against emerging deraining methods, such as those using contrastive learning [19] or self-supervised learning, would provide valuable insights into its relative strengths and weaknesses. Continuous comparison with state-of-the-art methods ensures that the system remains competitive and up-to-date with advancements in the field.

V. Summary

Future work in rain image restoration should focus on combining modern advancements in image restoration, efficient training strategies, and expanded applicability to address existing limitations. By integrating these improvements, the framework can evolve into a more generalized and practical solution for diverse environmental challenges.

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