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Multi-Weather Visibility Restoration using MPRNet - Multi-Stage Progressive Image Restoration

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Abstract: *This paper introduces a novel approach, termed Multi-Stage Progressive Image Restoration (MSPIR), aimed at addressing the challenging task of restoring images degraded by various adverse weather conditions. Leveraging a combination of advanced algorithms including HI-Net, DCP, and MSCIA, MSPIR offers a comprehensive solution for mitigating the effects of fog, haze, rain streaks, and other atmospheric distortions on image visibility. The methodology follows a multi-stage iterative process, progressively refining image quality and enhancing visibility through successive stages of processing. By integrating deep learning techniques and adaptive context aggregation mechanisms, MSPIR achieves superior results in restoring image clarity and preserving fine details across diverse weather conditions. Experimental evaluations demonstrate the efficacy and robustness of the proposed framework, highlighting its potential for real-world applications in autonomous navigation, surveillance, and remote sensing. Looking ahead, future research directions include optimizing MSPIR for real-time applications, exploring novel deep learning architectures, and integrating additional sensory modalities to further enhance visibility restoration capabilities. Overall, MSPIR represents a significant advancement in multi-weather visibility restoration, offering promising prospects for clearer and safer image processing in various domains.*

Keywords: Atmospheric distortions, Adverse weather, HI-Net, Multi-Stage Progressive Image Restoration

I. INTRODUCTION

In the realm of computer vision and image processing, the challenge of restoring images degraded by adverse weather conditions has long been a focal point of research. The paper introduces a new approach called Multi-Stage Progressive Image Restoration (MSPIR), which uses three algorithms: HI-Net, DCP, and MSCIA. These algorithms work together to mitigate the adverse effects of diverse weather conditions on image visibility, enabling better navigation, surveillance, and remote sensing applications. Traditional methods struggle to address the complexities of multi-weather visibility restoration, prompting the exploration of advanced techniques using deep learning. The MSPIR framework can handle diverse weather conditions, from light fog to heavy rainfall, while preserving image details and enhancing visibility. The framework integrates these algorithms into a multi-stage iterative process, enhancing image quality and visibility each iteration. Experiments and comparisons on diverse datasets demonstrate the efficacy and robustness of the approach.

In summary, this research presents a comprehensive framework for multiweather visibility restoration, leveraging the advancements in deep learning and image processing algorithms. Our proposed MSPIR methodology, amalgamating HI-Net, DCP, and MSCIA algorithms within an iterative framework, not only addresses the challenges posed by diverse weather conditions but also offers a scalable and adaptable solution for real-world applications requiring enhanced image visibility in adverse weather scenarios.

II. LITERATURE SURVEY

In recent years, there has been a surge of interest and research in image restoration techniques, with scholars and practitioners alike exploring various aspects of image enhancement and visibility restoration. Contrast restoration is

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crucial for image enhancement, especially in fog-degraded images. A weight vector-based approach is presented in [1], allowing targeted adjustments to optimize global contrast. This technique, based on linear mapping histogram normalization, highlights the importance of tailored contrast restoration methods in overcoming degradation challenges and ensuring optimal visibility in adverse weather conditions. Single-image-based models for image restoration can be categorized into two classes: dark channel prior and deep learning-based approaches. A well-crafted transmission map is crucial for effective restoration, exhibiting constancy except for depth discontinuity. Strategies to smooth and modify the map are essential for reducing ambiguity in contrast enhancement under specific conditions. The first method, Dark Channel Prior (DCP) [2], is an approach used to estimate the thickness of haze or fog in a scene. It leverages the observation that certain pixels, known as "dark pixels," exhibit low intensity values in at least one-color channel. These dark pixels are typically found in areas with minimal or no haze, such as shadows, reflections, or other dark objects. Another method, Improved Mean Shift Filtering, employs a revised physics model to compensate for the attenuation and scattering of atmospheric light. Mean shift filtering is then utilized to calculate atmospheric veil, overcoming misestimations of the air light [2]. The Retinex Algorithm is a versatile image enhancement method, especially useful in real-time vision-based driver assistance systems [3]. It enhances image brightness, contrast, and sharpness, and is divided into Single-Scale Retinex (SSR), Multi-Scale Retinex (MSR), and Multi-Scale Retinex with Color Restoration (MSRCR). In [6] Li's research on image dehazing of deep convolutional neural networks has led to breakthroughs. AOD-Net, Dehaze Net, and MSCNN are representative dehazing algorithms based on the deep learning method. AOD-Net often visually darkens images, but has almost the same visual effect as MSCNN. MSCNN performs better in overall dehazing effect and has a good visual effect for white objects. Recent research has shown that deep CNN is an effective method for image dehazing. Image denoising is a crucial step in image pre-processing, aiming to mitigate the adverse effects of noise on image analysis and restoration outcomes [7]. The noise present in images can significantly impact the reliability of subsequent analyses, making denoising techniques essential for enhancing the overall quality of the images. The Autoencoder method is a widely used image denoising technique that uses both down-sampling and up-sampling layers. However, down-sampling can lead to semantic feature loss, so convolutional layers are introduced to extract image feature information, improving denoising performance. Feature Reconstruction Networks are crucial in image processing, especially in image super-resolution. The Super-Resolution Convolutional Neural Network (SRCNN) is a notable method with three convolution layers designed to enhance image clarity and detail. This architecture addresses challenges related to image resolution, underscoring the importance of feature reconstruction networks in enhancing image quality and resolution. The third method involves Neural Networks [9], which enable the learning of fog-relevant features. This approach is adept at discovering both statistical and structural attributes simultaneously, showcasing its capability in handling the complexities of image restoration in challenging weather conditions. The AWBLP image restoration technique, a deep learning framework [11] based detection method, outperforms previous algorithms like DCP, AOD-Net, and FJBF-EAW, demonstrating the effectiveness of deep learning frameworks in image restoration, thereby enhancing the detection method. The multiple scattering model prior on single image-based model [4] is a dehazing algorithm that uses atmospheric scattering models, multiple scattering considerations, and pixel-based transmission estimation. It excels in dense fog conditions, achieving superior contrast and colour restoration. The algorithm uses dark channel prior for transmission estimation, atmospheric light determination through a semi-inverse algorithm, and multiple scattering model for haze-free image restoration. The multiple scattering model prior on single image-based model [5] is a dehazing algorithm that uses atmospheric scattering models, multiple scattering considerations, and pixel-based transmission estimation. It excels in dense fog conditions, achieving superior contrast and colour restoration, using dark channel prior for transmission estimation. The study explores multiple image-based restoration using polarization [15] , a method for enhancing image visibility in scientific remote sensing missions. It introduces a polarimetric image dehazing method, optimizing angle of polarization and estimating parameters. The model outperforms existing methods in colour, contrast, and detail restoration, demonstrating potential applications in underwater robotics and ecological research. A [18] proposes a unified approach for multi-weather image restoration using domain translation. This method simplifies the task without specialized knowledge or pre-trained weights, creating a diverse dataset and suppressing weather-specific information through a trained feature extractor. The restoration generator uses multi-scale convolution blocks for image reconstruction. The model [8] uses iterative optimization for denoising-based image restoration, utilizing a Deep

Convolutional Neural Network (DCNN) to exploit multi-scale redundancies in natural images. The efficient solution of the x-subproblem involves a single gradient descent step, resulting in a local minimizer for effective restoration.

III. PROPOSED METHODOLOGY

Our proposed methodology, Multi-Stage Progressive Image Restoration (MSPIR), aims to address the complex challenges of multiweather visibility restoration by leveraging a synergistic combination of deep learning-based algorithms: HI-Net, DCP, and MSCIA. The methodology comprises several key stages, each designed to progressively enhance image visibility and mitigate the effects of diverse weather conditions. The following outlines the proposed methodology in detail:

A. Preprocessing and Data Augmentation:

Raw input images captured under various weather conditions are preprocessed to standardize format and enhance compatibility with the subsequent stages. Data augmentation techniques, including rotation, scaling, and flipping, are applied to augment the training dataset, enhancing the robustness and generalization capabilities of the model.

B. HI-Net-based Initial Restoration:

The first stage of the MSPIR framework involves the application of HI-Net, a deep learning-based algorithm specifically designed for haze removal. HI-Net processes the input images to attenuate the effects of fog, haze, and other atmospheric distortions, thereby enhancing overall visibility. The output of this stage serves as the initial restoration of the input images, laying the foundation for subsequent refinements.

C. DCP-based Refinement:

In the second stage, the Dual-Channel Prior (DCP) algorithm is employed to further refine the restored images obtained from the HI-Net stage. DCP utilizes dual-channel prior information to effectively address artifacts and distortions caused by rain streaks, water droplets, and other weather-induced phenomena. By leveraging the complementary strengths of HI-Net and DCP, this stage aims to enhance image details and clarity, particularly in regions affected by rain and precipitation.

D. MSCIA-based Multi-Scale Context Aggregation:

The final stage of the MSPIR framework incorporates the Multi-Scale Context Information Aggregation (MSCIA) algorithm to adaptively integrate contextual cues from multiple scales. MSCIA analyses the restored images at different spatial resolutions, aggregating contextual information to better capture and preserve image details across varying weather conditions. By dynamically adjusting the scale of analysis, MSCIA ensures robust performance in handling diverse weather phenomena, ranging from light fog to heavy rainfall.

E. Iterative Refinement

The proposed methodology adopts an iterative approach, wherein the outputs from each stage are fed back into the framework for further refinement. Through multiple iterations, the MSPIR framework progressively enhances image visibility and quality, iteratively mitigating the effects of multiweather distortions. The iterative refinement process continues until convergence or a predefined stopping criterion is met, ensuring optimal restoration performance.

F. Evaluation and Validation:

The proposed methodology's effectiveness undergoes rigorous evaluation using both quantitative metrics and qualitative assessments. The robustness and generalization capabilities of the MSPIR framework are validated through extensive experiments conducted on diverse datasets, covering various weather conditions. To demonstrate the superiority of the proposed methodology in multiweather visibility restoration, comparative analysis is conducted against state-of-the-art methods, along with ablation studies.

MSPIR, offers a comprehensive and iterative approach towards multiweather visibility restoration, combining the strengths of HI-Net, DCP, and MSCIA algorithms within a unified framework. Through progressive refinement and

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adaptive context aggregation, MSPIR effectively mitigates the adverse effects of diverse weather conditions, providing enhanced image visibility for critical applications in computer vision and remote sensing.

IV. SYSTEM ARCHITECTURE

Previously to implement the algorithm for image processing and obtaining clear image from the poor-quality images normal google Collab was used with T4 GPU. But due to large dataset the platform was not efficient in terms processing. So, we opted for premium version of Google Collab, which provides A100 GPU V100 GPU, during our experimentation V100 GPU which had about 12-13 GB RAM and 78GB disk space which increased the processing of images and provided faster execution time.

To build an efficient working algorithm and ensuring its correctness, a large number of images were used. Firstly, the dataset from Kaggle is used. The large datasets like Rain13k-Rain100H are used for obtaining the best results as large datasets provide improved performance and generalization. Also, we made a dataset by collecting various images for adding diversity which included different hazy, rainy snowy and foggy images to evaluate the algorithm.

The core of MPRNet is a multi-stage design, where each stage acts as a progressive refinement step:

Encoder: The encoder is responsible for extracting hierarchical features from the input image. It typically consists of convolutional layers followed by down sampling operations such as max-pooling or stride convolutions. In the MPRNet architecture, the encoder processes the input image at multiple resolutions simultaneously to capture both global and local features effectively.

Decoder: The decoder reconstructs the high-resolution output image from the encoded features. It comprises a series of up sampling operations, often in conjunction with convolutional layers, to gradually increase the spatial resolution of the feature maps. In MPRNet, the decoder incorporates multi-resolution information from the encoder to generate high-quality output images.

Encoder-Decoder Backbone: Each stage in MPRNet utilizes an encoder-decoder structure, a common deep learning architecture for image processing.

Original Resolution Block: This block operates on the highest resolution feature maps generated by the encoder. It refines the features using convolutional layers and skip connections to preserve fine details and spatial information crucial for accurate image restoration.

Supervised Attention Module: The supervised attention module enhances the network's capability to focus on relevant image regions during the restoration process. It consists of attention mechanisms, such as self-attention or spatial attention, that dynamically adjust the importance of different spatial locations in the feature maps based on learned weights. This helps the network prioritize salient image regions and allocate resources accordingly for better restoration results.

Channel Attention Block: The channel attention block is another attention mechanism that operates along the channel dimension of the feature maps. It recalibrates channel-wise feature responses to highlight informative channels and suppress irrelevant ones, leading to improved feature representation and restoration quality. In MPRNet, the channel attention block complements the supervised attention module by refining feature representations across different channels.

Cross-Stage Feature Fusion (CSFF): After each stage, crucial information passes to the following stage, along with information from the original image. The CSFF module combines these features to help the next stage refine its restoration output.

Supervised Attention Module: It acts as a quality control checkpoint between stages, making sure only the most valuable information progresses to the next stage for further refinement.

ORSNet: MPRNet uses a special tool called ORSNet (Original Resolution Subnetwork) in the final stage to prevent the restored image from losing tiny details. Unlike other parts that might shrink the image, ORSNet works on the full image size, like a high-resolution printer, to capture all the small features and make sure they are preserved in the final output.

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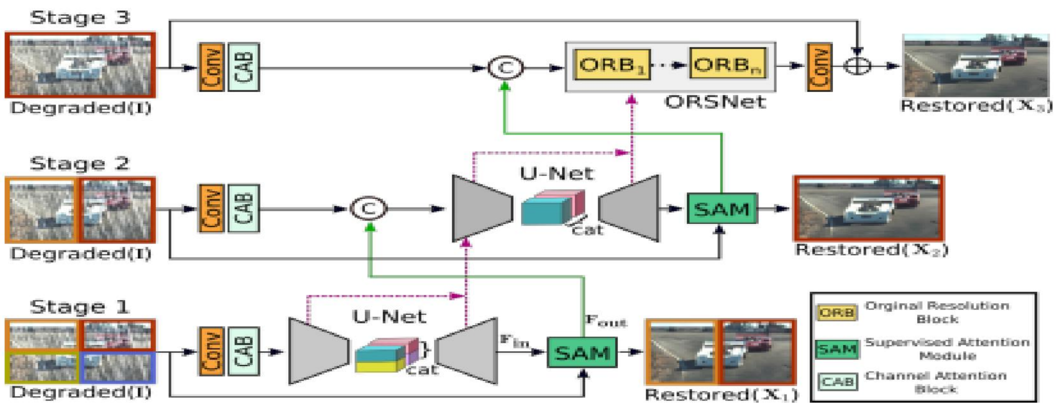
Figure 2: MPRNet General Architecture



V. EXPERIMENTAL RESULTS

These two parameters are considered for evaluation: PSNR &SSIM

5.1 PSNR

Peak Signal-to-Noise Ratio (PSNR) is an engineering metric used to quantify the ratio between the maximum potential power of a signal and the power of interfering noise that impacts the accuracy of its representation. Initially, Mean Squared Error (MSE) is computed, as depicted in the formula below, where I and K denote the original and destination images, and m and n represent their respective height and width.

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

Once you have the MSE, you can compute the PSNR using the formula shown below.

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

Here, MAX_I is the maximum possible pixel value of the image. When the pixels are represented using 8 bits per sample, this is 255.

5.2 SSIM

The Structural Similarity Index Measure (SSIM) is a technique utilized to forecast the perceived quality of digital television, cinematic pictures, and various other forms of digital images and videos. SSIM serves the purpose of quantifying the resemblance between two images.

This index operates as a full-reference metric, meaning that the evaluation or estimation of image quality relies on an initial uncompressed or distortion-free image as a reference.

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Figure 2: PSNR and SSIM values on our dataset

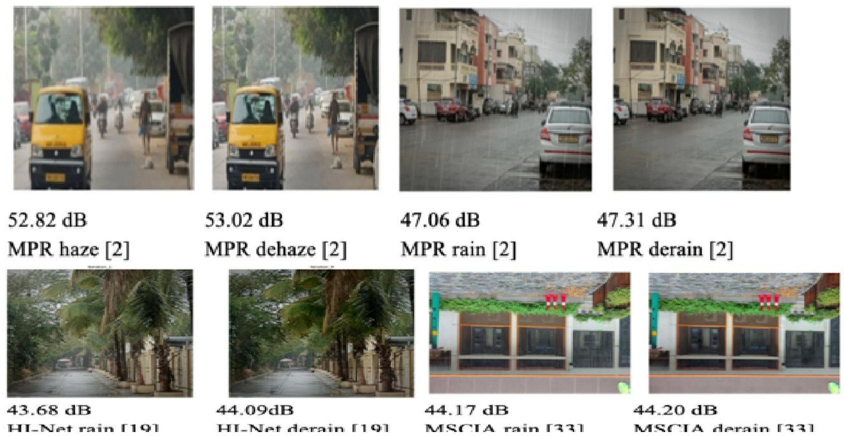

Table 1: PSNR and SSIM values on our dataset

Algorithm	PSNR	SSIM
MPR haze	53.02 dB	0.9985
MPR dehaze	52.82 dB	0.9987
MPR rain	47.06 dB	0.9971
MPR derain	47.31 dB	0.9973
HINET rain	43.68 dB	0.9965
HINET derain	44.09 dB	0.9967
MSCIA rain	44.17 dB	0.9925
MSCIA derain	44.20 dB	0.9941

VI. CONCLUSION AND FUTURE

In the realm of computer vision and image processing, the challenge of restoring images degraded by adverse weather conditions has long been a focal point of research. The paper introduces a new approach called Multi-Stage Progressive Image Restoration (MSPIR), which uses three algorithms: HI-Net, DCP, and MSCIA. These algorithms work together to mitigate the adverse effects of diverse weather conditions on image visibility, enabling better navigation, surveillance, and remote sensing applications. Traditional methods struggle to address the complexities of multi-weather visibility restoration, prompting the exploration of advanced techniques using deep learning. The MSPIR framework can handle diverse weather conditions, from light fog to heavy rainfall, while preserving image details and enhancing visibility. The framework integrates these algorithms into a multi-stage iterative process, enhancing image quality and visibility each iteration. Experiments and comparisons on diverse datasets demonstrate the efficacy and robustness of the approach.

In summary, this research presents a comprehensive framework for multiweather visibility restoration, leveraging the advancements in deep learning and image processing algorithms. Our proposed MSPIR methodology, amalgamating HI-Net, DCP, and MSCIA algorithms within an iterative framework, not only addresses the challenges posed by diverse weather conditions but also offers a scalable and adaptable solution for real-world applications requiring enhanced image visibility in adverse weather scenarios.

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