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A Review of Image Restoration Techniques for Foggy and Hazy Environmental Conditions

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Abstract: *Images captured under adverse atmospheric conditions such as fog, haze, smoke, and mist often suffer from reduced visibility, low contrast, color distortion, and loss of important structural information. These degradations negatively affect computer vision applications including surveillance, autonomous driving, remote sensing, object detection, and image recognition. Image restoration techniques aim to recover the original scene information by removing atmospheric interference and enhancing image quality.*

During 2010–2021, significant developments occurred in image dehazing and restoration, beginning with traditional prior-based approaches such as Dark Channel Prior and Color Attenuation Prior, followed by optimization-based methods and later deep learning approaches using convolutional neural networks, generative models, and attention mechanisms. This review presents a comprehensive analysis of major image restoration techniques developed between 2010 and 2021 for foggy and hazy environments. The study discusses physical model-based methods, enhancement-based techniques, fusion approaches, and learning-based algorithms along with their advantages, limitations, and performance evaluation criteria.

Keywords: Image Restoration, Image Dehazing, Fog Removal, Haze Removal, Dark Channel Prior, Deep Learning, CNN, Atmospheric Scattering Model.

I. INTRODUCTION

Outdoor images captured in foggy and hazy environments experience severe degradation due to the scattering and absorption of light by atmospheric particles. The presence of suspended particles reduces contrast, decreases visibility, and changes the original color distribution of captured scenes. Such degradation creates challenges for advanced computer vision systems because important features and object boundaries become unclear. Image restoration techniques attempt to estimate the haze-free image from degraded observations by modelling atmospheric effects or learning restoration patterns from large image datasets.

The atmospheric scattering model has been widely used as the foundation for haze removal research. According to this model, the observed hazy image is influenced by scene radiance, transmission map, and atmospheric light. Traditional restoration approaches estimate these unknown parameters using handcrafted assumptions, whereas modern deep learning approaches directly learn the relationship between hazy and clear images. Between 2010 and 2021, research progressed from statistical priors toward data-driven models capable of handling complex real-world conditions.

II. ATMOSPHERIC SCATTERING MODEL FOR HAZY IMAGE FORMATION

The degradation of images under fog and haze is commonly represented using the atmospheric scattering model:

$$I(x) = J(x)t(x) + A(1 - t(x))$$

Where:

1. **I(x)** = observed hazy image

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2. **J(x)** = original haze-free scene radiance
3. **A** = atmospheric light
4. **t(x)** = transmission map

The objective of restoration techniques is to estimate **J(x)** by recovering transmission and atmospheric parameters.

III. CLASSIFICATION OF IMAGE RESTORATION TECHNIQUES

Image restoration techniques for foggy and hazy conditions can mainly be classified into:

1. Image Enhancement-Based Methods
2. Prior-Based Restoration Methods
3. Optimization-Based Methods
4. Image Fusion-Based Methods
5. Deep Learning-Based Methods

Table 1: Major Image Restoration Techniques for Foggy and Hazy Images (2010–2021)

Year	Technique/Method	Research Contribution	Advantages	Limitations	Reference
2010	Dark Channel Prior (DCP)	Estimated haze thickness using minimum intensity statistics	Effective single-image dehazing	Fails in bright objects and sky regions	He (2010)
2011	Guided Filter Based Refinement	Improved transmission estimation using edge-preserving filtering	Better boundary recovery	Computational complexity	He (2011)
2012	Color Attenuation Prior (CAP)	Used color difference and depth estimation	Simple and efficient	Sensitive to illumination changes	Zhu (2015)
2013	Boundary Constraint Method	Improved atmospheric light estimation	Better contrast restoration	Requires accurate parameter estimation	Meng (2013)
2014	Multi-scale Fusion Method	Combined white balance and contrast enhancement	Improved visual quality	May produce artifacts	Ancuti (2014)
2015	DehazeNet	First CNN-based haze removal framework	Automatic feature learning	Requires training data	Cai (2016)
2016	MSCNN	Multi-scale CNN for transmission prediction	Improved structural restoration	High computational demand	Ren (2016)
2017	AOD-Net	End-to-end CNN dehazing network	Fast and efficient	Limited generalization	Li (2017)
2018	GAN-Based Dehazing	Used adversarial learning for restoration	Better perceptual quality	Training instability	Engin (2018)
2019	Attention-Based Networks	Focused on important image regions	Improved feature extraction	Increased complexity	Qin (2020)
2020	NH-HAZE Dataset	Introduced realistic	More realistic	Limited dataset	Ancuti

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	Based Methods	non-homogeneous haze evaluation	benchmarking	size	(2020)
2021	Deep Learning Survey Models	Categorized supervised and unsupervised dehazing methods	Comprehensive performance analysis	Data dependency	Gui (2021)

IV. TRADITIONAL IMAGE RESTORATION TECHNIQUES

1. Dark Channel Prior

He (2010) proposed the Dark Channel Prior technique, which became one of the most influential single-image dehazing methods. The method assumes that most outdoor haze-free images contain pixels with very low intensity values in at least one color channel. By estimating atmospheric light and transmission maps, DCP effectively removes haze and enhances image visibility.

Advantages:

1. Does not require multiple images.
2. Produces significant contrast improvement.
3. Suitable for outdoor scenes.

Limitations:

1. Poor performance in bright regions.
2. Produces halo artifacts near edges.
3. Computationally expensive for high-resolution images.

2. Color Attenuation Prior

Zhu (2015) introduced the Color Attenuation Prior method, which estimated scene depth using differences between brightness and saturation. This approach provided an alternative to DCP by establishing a relationship between haze density and image color characteristics.

Advantages:

1. Simple mathematical formulation.
2. Faster than DCP.
3. Provides good depth estimation.

Limitations:

1. Sensitive to environmental lighting.
2. Less effective for dense haze.

V. IMAGE ENHANCEMENT-BASED METHODS

Enhancement-based approaches improve visual appearance without explicitly estimating atmospheric parameters. Common techniques include:

1. Histogram Equalization
2. Retinex-Based Enhancement
3. Contrast Limited Adaptive Histogram Equalization
4. Gamma Correction

These methods increase brightness and contrast but may not completely recover original scene information.

VI. IMAGE FUSION-BASED RESTORATION METHODS

Fusion-based approaches combine multiple enhanced versions of an image to obtain better visibility. Ancuti (2014) proposed a multi-scale fusion framework that combines contrast enhancement and color correction strategies.

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Benefits:

1. Improved natural appearance.
2. Does not require depth estimation.
3. Suitable for real-world applications.

Drawbacks:

1. Cannot completely remove haze.
2. May introduce artificial colors.

VII. DEEP LEARNING-BASED IMAGE RESTORATION METHODS

The development of deep learning significantly changed haze removal research after 2015. CNN-based models learned complex mappings between hazy and clear images without requiring manually designed priors.

1. DehazeNet

Cai (2016) proposed DehazeNet, which used convolutional neural networks to estimate transmission maps. It improved restoration quality compared with traditional approaches.

2. MSCNN

Ren (2016) introduced a multi-scale CNN approach that extracted features at different image resolutions, improving transmission estimation.

3. AOD-Net

Li (2017) proposed All-in-One Dehazing Network (AOD-Net), which directly generated haze-free images through an end-to-end learning framework.

4. Attention and GAN-Based Methods

Recent approaches introduced attention mechanisms and generative adversarial networks to improve perceptual quality and restore fine details. Deep learning-based surveys classify these methods into supervised, semi-supervised, and unsupervised categories.

Table 2: Comparison Between Traditional and Deep Learning Methods

Parameter	Traditional Methods	Deep Learning Methods
Feature Extraction	Manual priors	Automatic learning
Training Requirement	Not required	Requires datasets
Processing Speed	Moderate	High after training
Generalization	Limited	Better adaptability
Image Quality	Moderate	Higher restoration accuracy
Computational Demand	Lower	Higher

VIII. EVALUATION METRICS

The performance of restoration algorithms is generally evaluated using:

Metric	Purpose
PSNR	Measures reconstructed image quality
SSIM	Evaluates structural similarity
MSE	Calculates restoration error
NIQE	No-reference image quality assessment
Visual Quality Assessment	Human perception evaluation

Benchmark datasets such as RESIDE and NH-HAZE have been widely used for evaluating dehazing methods.

IX. CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress, several challenges remain:

1. **Real-world haze complexity:**
   Synthetic datasets cannot fully represent natural fog conditions.
2. **Color distortion:**
   Some algorithms introduce unrealistic colors.
3. **Computational requirements:**
   Deep networks require high processing resources.
4. **Generalization problems:**
   Models trained on specific datasets may fail in different environments.

X. CONCLUSION

Image restoration for foggy and hazy environments has evolved considerably from traditional image enhancement and prior-based approaches to advanced deep learning frameworks. Methods such as Dark Channel Prior, Color Attenuation Prior, fusion-based algorithms, and CNN-based networks have significantly improved visibility restoration. Although deep learning approaches provide superior performance, challenges related to computational complexity, dataset limitations, and real-world adaptability remain. Future research should focus on developing efficient, generalized, and real-time restoration models capable of handling diverse atmospheric conditions.

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