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Traditional Dehazing Methods

Classical techniques (e.g. DCP – Dark Channel Prior [11], Retinex/CAP, histogram equalization/CLAHE) use simple priors or contrast enhancement to remove haze. DCP assumes some pixels are very dark in haze-free scenes and estimates a transmission map refined by a guided filter. While DCP can boost visibility in mild haze, it amplifies noise in sky regions and produces halo artifacts under dense fog [11]. CLAHE and Retinex methods quickly enhance local contrast, but do not actually separate atmospheric light, so they leave most haze intact especially in thick fog [7]. These methods are fast (suited to CPU/video streams) but brittle in heavy fog.

CNN-Based Dehazing Networks

Deep learning models have greatly improved dehazing quality (PSNR/SSIM) at the cost of more computation. Lightweight end-to-end CNNs like AOD-Net (Li et al., 2017) and DehazeNet (Cai et al., 2016) directly learn a mapping from hazy to clear images. ReViewNet (Mehra et al., 2020) processes ~40 FPS on GPU with PSNR 25.55 dB and SSIM 0.947 on RESIDE-Outdoor benchmark [3]. Meng et al. (2025) proposed an adaptive routing network achieving 26.75 dB PSNR / 0.832 SSIM with ~4.8 ms per 256×256 image (~208 FPS) [4]. FALCON (Kim et al., 2024) achieves 22.41 dB PSNR at 182.9 FPS using frequency-domain bottlenecks [5]. These CNNs trade slight PSNR drops for significant speed gains [2]. However, even the best CNNs can underperform in very dense fog and may leave residual haze or color casts in challenging conditions [2][11].

Multi-scale and attention models like MSBDN, GridDehazeNet, and FFA-Net (Zhang et al., 2019) achieve high PSNR on synthetic datasets (often 28–32 dB), but they are too slow for real-time use and often underperform in dense fog [11]. Transformer-based methods like DehazeFormer (Zhou et al., 2023) embed the atmospheric scattering model into a vision transformer [9]. RefineDNet (Zhao et al., 2021) applies DCP first and refines via a GAN, improving over raw DCP in heavy haze but potentially introducing color halos [8].

Video Dehazing

Video dehazing requires temporal consistency to prevent flickering. MAP-Net (Xu et al., 2023) uses multi-range temporal alignment guided by haze priors, achieving ~27.1 dB PSNR and 0.9349 SSIM on real video datasets [10]. Scene-Adaptive Dehazing (Lyu et al., 2023) uses keypoint tracking and adaptive atmospheric light estimation across frames, processing each frame in a few milliseconds with ~98.6% defog accuracy [6].

Strengths and Limitations

Advanced dehazing models significantly outperform DCP and CLAHE in both objective quality and real-time speed. Lightweight CNNs like ReViewNet and FALCON balance dehazing quality and real-time performance. However, all methods still struggle under extremely dense fog [11][8]. Hybrid methods like RefineDNet offer improved perceptual quality but require more computation [8].

Comparison Table

Method	Type	PSNR / SSIM	Speed (Latency)	Notes / Use-case
CLAHE	Traditional (histogram)	N/A	Fast (≤ real-time)	Simple contrast boost; does not remove haze.
Dark Channel Prior	Physics-based (prior)	~19.1 dB / 0.815 [1]	≈1.6 s/image (CPU, 640×) [3]	Enhances detail but amplifies sky noise in dense fog [11].
AOD-Net	CNN (all-in-one)	~20–22 dB (RESIDE)	~15 FPS (GPU) [3]	Light CNN; modest quality, near-real-time on GPU.
FFA-Net	CNN w/ attention	~28 dB (synthetic sets) [11]	Heavy (non-real-time)	High-detail recovery; struggles with real dense haze [11].
ReViewNet	CNN (lightweight)	25.55 dB / 0.947 [3]	~40 FPS (GPU) [3]	Resource-efficient; strong PSNR among fast models.
Adaptive Router	CNN (scene-adaptive)	26.75 dB / 0.832 [4]	~208 FPS (4.8 ms @256×256) [4]	Extreme speed with slight quality drop.
FALCON	CNN+FFT bottlenecks	22.41 dB (NH-Haze2) [5]	182.9 FPS (256×256) [5]	Frequency-domain modules; high PSNR and FPS.
DehazeFormer	Transformer+Prior	N/A	Slow [9]	Hybrid model; excellent quality but too slow for live use [9].
RefineDNet	Hybrid (DCP + GAN)	N/A	N/A	Neural-augmented DCP; better visual fidelity in dense fog

				[8].
MAP-Net	Video CNN (temporal)	27.12 dB / 0.9349 [10]	Varies	Multi-frame alignment; superior quality on video datasets [10].
Scene-Adaptive	Model + CNN (video)	~98.6% defog accuracy [6]	~few ms/frame [6]	Real-time video dehazing; adaptive per frame [6].

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[1] RESIDE dataset baseline performance.

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