DOMAIN ADAPTIVE DEHAING BASED ON PHYSICAL PROPERTIES

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Annotation. Deep learning-based single image dehazing has advanced significantly, yet models trained on synthetic data struggle in real-world scenarios. To address this cross-domain gap, we propose a Synthetic-to-Real Dehazing framework comprising two key components: 1) A domain adaptation network that generates Synthetic-to-Real hazy images by learning real haze characteristics through depth-transmission map correlations, and 2) A physics-guided dehazing network based on the atmospheric scattering model. Crucially, our framework requires no real hazy data during dehazing training. Experiments demonstrate our framework's superior cross-domain dehazing generalization.

Keywords. *Image hazing/dehazing, Deep learning, Image enhancement, Domain adaptation, Image restoration.*

Haze, caused by atmospheric water droplets, degrades computer vision tasks (e.g., object detection, image segmentation) through light attenuation and scattering. This drives the importance of single image dehazing research. The atmospheric scattering model [1] formalizes this phenomenon as:

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

where I is observed hazy image, J is scene radiance, t is transmission map, and A is atmospheric light.

Deep learning has advanced single image dehazing, yet most methods rely on paired hazy/clear images that are impractical to acquire in real settings. While synthetic datasets circumvent this need, their simplified haze simulations lack real-world complexity, resulting in domain gaps that degrade performance on natural hazy images. Based on this problem, we propose the cross-domain dehazing framework. The framework is divided into two parts: data synthesis more in line with real haze characteristics and haze removal.

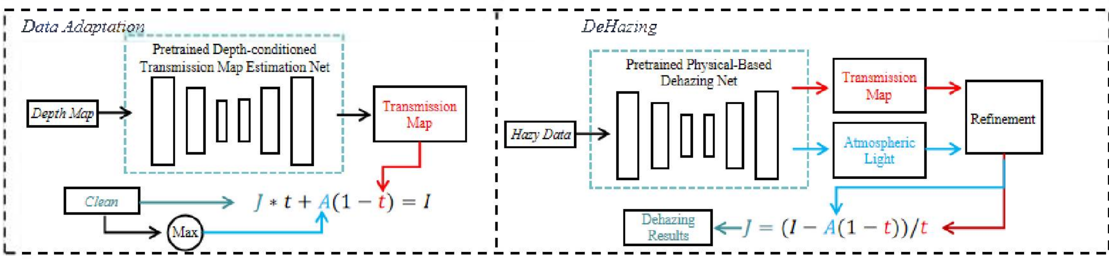
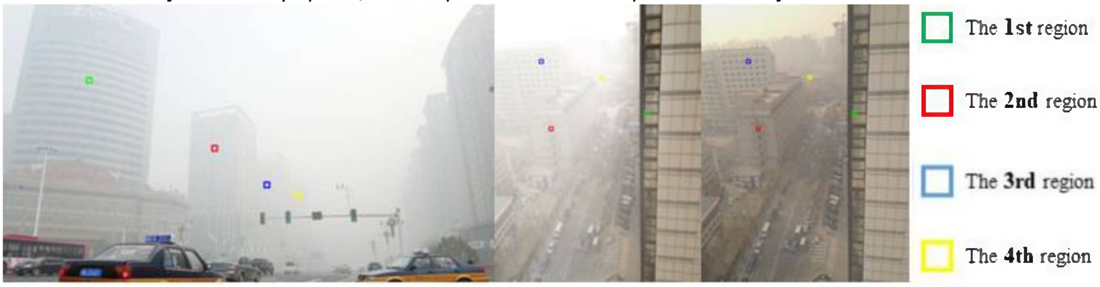


Figure 1 – Framework flow chart. The framework consists of two parts: 1. cross-domain data synthesis and single image dehazing.

The proposed dehazing framework, as illustrated in Figure 1, comprises two core components: a domain-adaptive data synthesis module and a dual-stage dehazing network. In the data synthesis phase, we establish a novel physical correlation model among the scattering coefficient β, transmission map t, and scene depth map d, where $t=e^{-\beta d}$. A pretrained depth-conditioned transmission map estimation network dynamically adjusts the scattering coefficient β through adaptive optimization algorithms. This process integrates scene depth information d [2] to generate physically accurate transmission maps that faithfully replicate real-world haze dispersion characteristics. By substituting the synthesized transmission map t and haze-free images J into the atmospheric scattering model (Equation 1), we efficiently construct the cross-domain datasets, providing robust training data for subsequent network optimization.



(a) Real Hazy Data (b) Ours (c) Baseline [5] (d) Region

Figure 2 – The 4 regions demonstrate the superiority of our synthetic data through comparative analysis (across four depth regions) against real haze data and baseline methods [5], validating that our results naturally reflect haze concentration attenuation with scene depth.

The dehazing network architecture adopts a two-stage progressive processing pipeline. Initially, hazy images are processed through a physical based dehazing network to obtain initial transmission estimates *t* and atmospheric light estimates *A*. Subsequently, a refinement module optimizes these parameters, yielding precise transmission map *t* and atmospheric light *A*. The optimized physical parameters are then incorporated into the equation (inverse form of Equation 1) to reconstruct high-quality haze-free images.

(a) Hazy (b) C2P Net [3] (c) DCP [4] (d) Ours

Figure 3 – Visual comparison of dehazing results of different methods.

Extensive experimental validation confirms the effectiveness of our proposed dehazing framework (detailed presentation is omitted here due to space constraints). The cross-domain synthesis method efficiently constructs domain-adaptive training data to enhance model robustness, while the dual-stage network accurately estimates transmission map *t* and atmospheric light *A*, achieving high-quality restoration.

Reference:

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