RPD-Diff: Region-Adaptive Physics-Guided Diffusion Model for Visibility Enhancement under Dense and Non-Uniform Haze

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Section 1: Challenges/Contribution

Challenges

Previous applications of DDPMs to the dehazing task exhibit critical limitations, particularly when confronted with dense and non-uniform haze, which are caused by the following two reasons.

- **(1) Insufficient Conditioning: Direct conditioning on hazy images is suboptimal for dense haze due to severe information loss. Weak signals hinder the direct noise-to-clear image generation, causing detail loss and slow convergence.**
- **(2) Lack of Spatial Adaptivity: Standard DDPMs apply uniform processing, failing to adapt to the spatial heterogeneity of non-uniform haze (varying density), which prevents accurate and effective restoration in complex areas.**

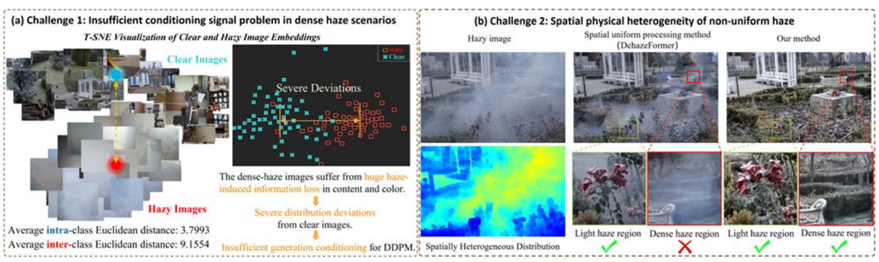


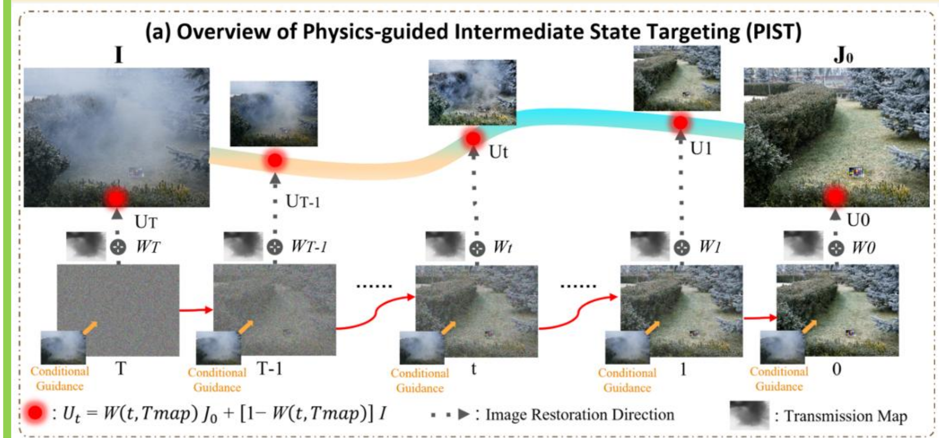
Figure 2: Challenges in dehazing under scenarios of dense and non-uniform haze.

Contribution

- **WeproposeaRegion-adaptivePhysics-guided Dehazing Diffusion Model (RPD-Diff), which takes full advantage of the physical priors associated with dense and non-uniform haze to achieve high-quality visibility enhancement.**
- **We propose Physics-guided Intermediate State Targeting (PIST). PIST uses physical priors to adaptively refine regional Markov transitions. This task transformation effectively solves the insufficient conditioning issue in dense haze.**
- **We develop the adaptive Haze-Aware Denoising Timestep Predictor (HADTP) that dynamically adjusts patch-specific denoising timestep leveraging a transmission map cross-attention mechanism, which effectively addresses the spatial physical heterogeneity inherent in non-uniform haze.**

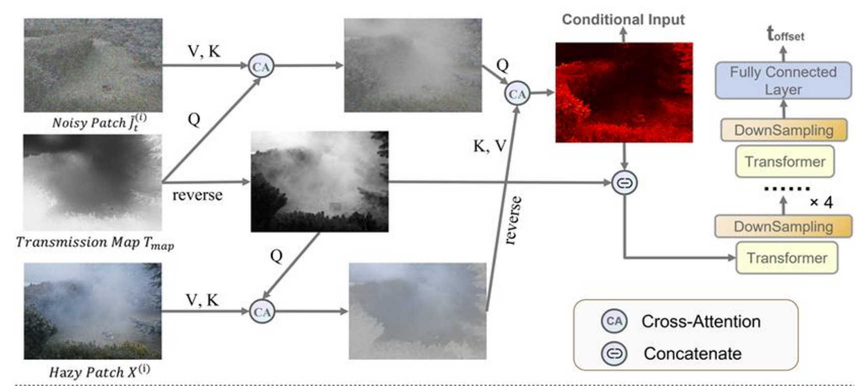
Section 2: Methods

(1) Overview of our Physics-guided Intermediate State Targeting (PIST).



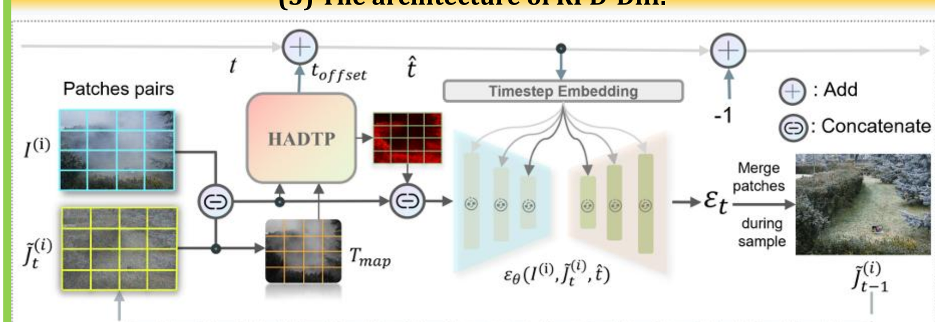
We introduce an intermediate state Ut that varies with the Timestep t, which simplifies the reconstruction task by targeting this intermediate state.

(2) Overview of our Haze-Aware Denoising Timestep Predictor (HADTP)



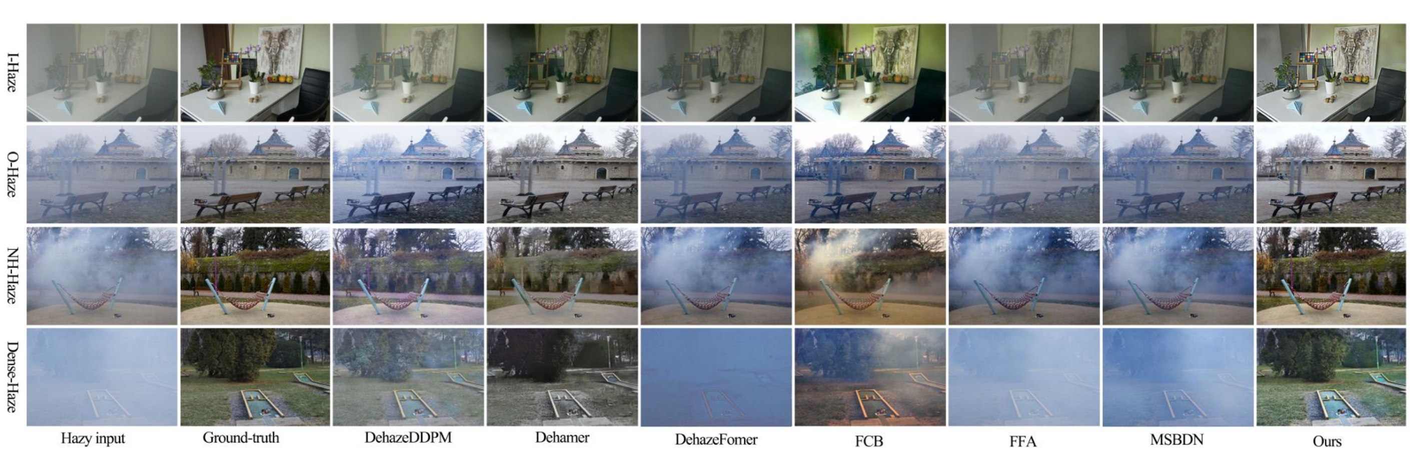
We introduce a Tmap-based cross-attention mechanism called HADTP . HADTP serves two functions: it enhances the dehazing guidance condition, and simultaneously outputs a timestep offset toffset to modulate the dehazing intensity for regions with varying haze concentrations.

(3) The architecture of RPD-Diff.



At each timestep t, the Haze-Aware Denoising Timestep Predictor(HADTP) first adjusts the denoising timestep and generates enhanced conditional input employing a transmission map cross-attention mechanism. Subsequently, the model restores the image Jt−1 from Jt, utilizing the estimated even noise εt.

Section 3: Experiments



Qualitative results on the Dense-Haze, Non-Homogeneous Haze, O-Haze, and I-Haze datasets demonstrate the effectiveness of our approach. Under real-world conditions with dense and non-homogeneous haze, prior dehazing methods often result in residual haze and color distortions. In contrast, our RPD-Diff model produces high-quality, haze-free images with sharp edges and minimal haze artifacts.