NEURAL INFORMATION PROCESSING SYSTEMS

Degradation-aware Dynamic Schrödinger Bridge for Unpaired Image Restoration

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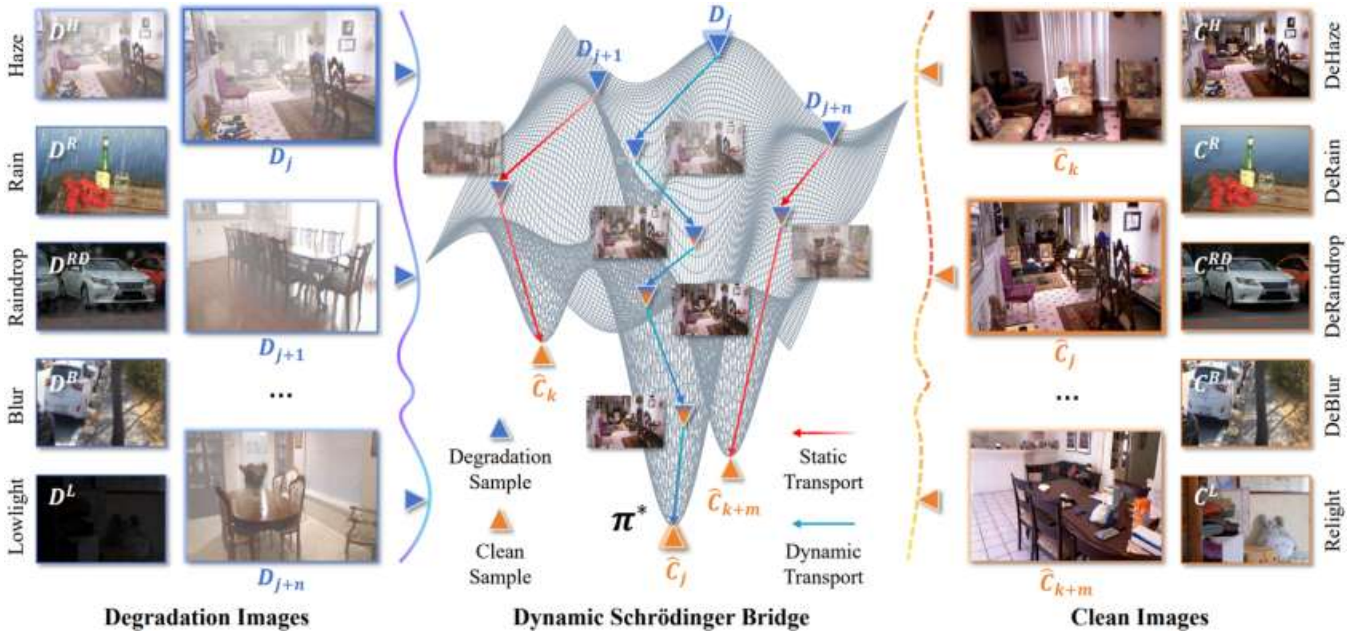
Problem Statement

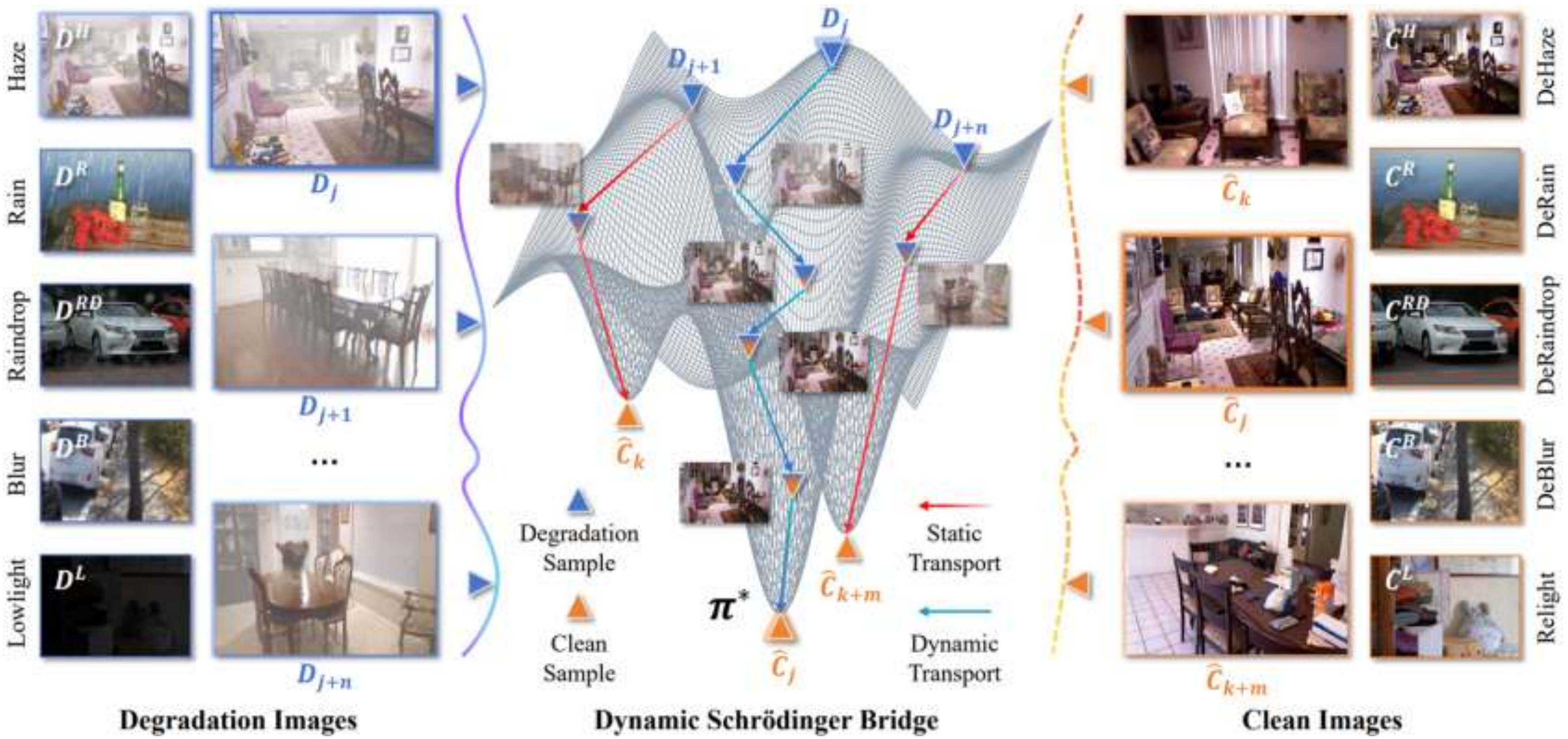
- Unpaired image restoration must map from real degraded domains (rain, haze, blur, low-light, etc.) to clean images without paired supervision.
- Prior approaches ignore degradation consistency, which can accumulate artifacts along the transport trajectory.



Motivation

Key Idea: Schrödinger Bridge (SB) between image distributions

- Transport from degraded → clean image distribution
- Works with unpaired data



Background

- What's Schrödinger Bridge (SB)?

Schrödinger Bridge. Given two probability distributions π_0 and π_1 over $\mathbb{R}^d$, the Schrödinger Bridge problem seeks the most likely stochastic trajectory $\{\boldsymbol{x}_t\}_{t\in[0,1]}$ that evolves from π_0 to π_1. Let Ω denote the space of continuous paths in $\mathbb{R}^d$, and let $\mathcal{P}(\Omega)$ represent the collection of path measures. The SB problem can be formulated as the following entropy-regularized variational problem:

$$\mathbb{Q}^\star = \arg\min_{\mathbb{Q}\in\mathcal{P}(\Omega)} \mathrm{KL}(\mathbb{Q}\,\|\,\mathbb{W}^\tau) \quad \text{s.t.} \quad \mathbb{Q}_0 = \pi_0, \quad \mathbb{Q}_1 = \pi_1, \tag{1}$$

where $\mathbb{W}^\tau$ is the Wiener measure with diffusion parameter τ, and $\mathbb{Q}_t$ represents the marginal at time t. The solution $\mathbb{Q}^\star$ defines the Schrödinger Bridge connecting π_0 to π_1.

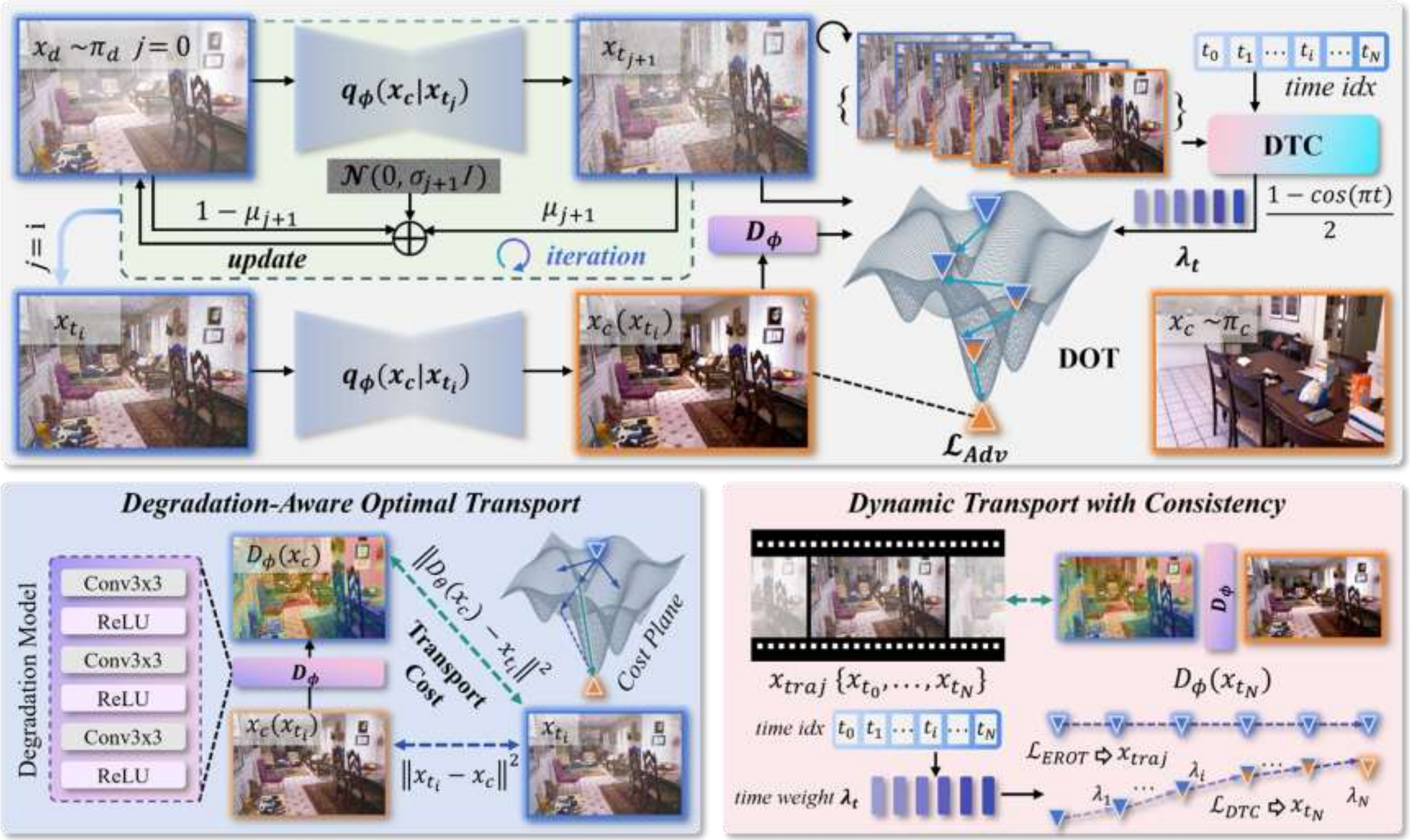
Two perspectives—stochastic control and static coupling—offer foundational insight into the SB problem and guide our model design. Both are central to understanding the shortcomings of prior SB methods and motivating our approach.

Stochastic Control Formulation. From the viewpoint of stochastic control [33], the SB process $\{\boldsymbol{x}_t\} \sim \mathbb{Q}^\star$ satisfies a stochastic differential equation $d\boldsymbol{x}_t = \boldsymbol{u}_t^\star dt + \sqrt{\tau} d\boldsymbol{w}_t$, where $\boldsymbol{u}_t^\star$ is the optimal control minimizing the expected energy of the drift:

$$\boldsymbol{u}_t^\star = \arg\min_{\boldsymbol{u}} \mathbb{E}\left[\int_0^1 \frac{1}{2}\|\boldsymbol{u}_t\|^2 dt\right] \quad \text{s.t.} \quad \begin{cases} d\boldsymbol{x}_t = \boldsymbol{u}_t dt + \sqrt{\tau} d\boldsymbol{w}_t \\ \boldsymbol{x}_d \sim \pi_0, \quad \boldsymbol{x}_c \sim \pi_1. \end{cases} \tag{2}$$

Framework Overview

Degradation-Aware Dynamic Schrödinger Bridge （DDSB）



Method Design

Two Novel Components:

1️⃣ Degradation-aware Optimal Transport (DOT)

- Learns inverse degradation model
- Reduces error accumulation

2️⃣ Dynamic Transport with Consistency (DTC)

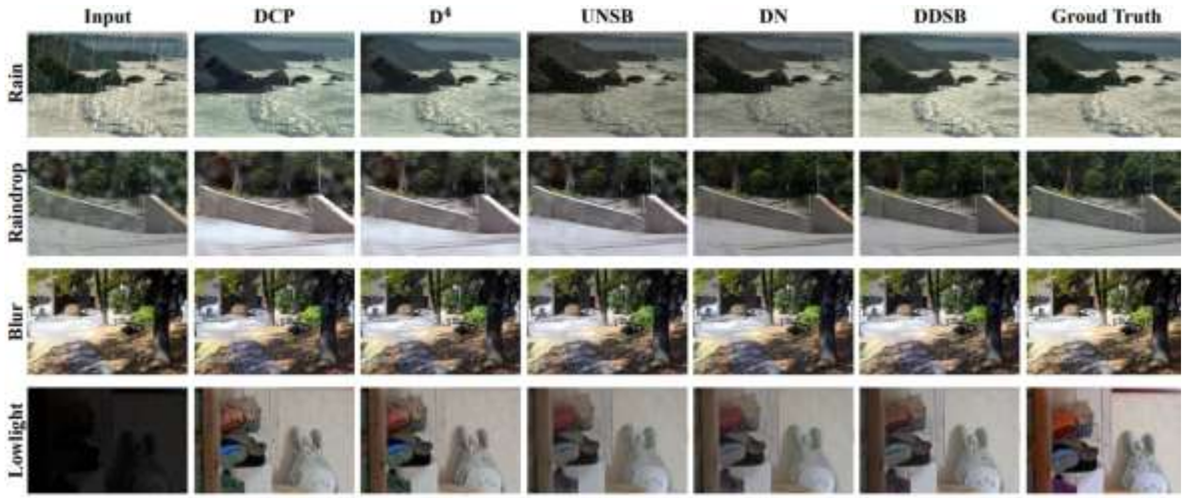
- Emphasizes early restoration stages
- Preserves image details throughout process

Experiment

- Experiment 1: Multi-Task Restoration

Table 1: Quantitative comparison of DDSB with the state-of-the-art unpaired image restoration methods on multi-task restoration. Top three results are highlighted as **best**, second and third.

Method	Derain [52]		Deraindrop [34]		Lowlight [48]		Deblur [31]	
	PSNR (dB)	SSIM	PSNR (dB)	SSIM	PSNR (dB)	SSIM	PSNR (dB)	SSIM
DCP [16]	13.25	0.705	18.92	0.752	15.93	0.743	12.97	0.702
CycleGAN [59]	21.28	0.796	20.55	0.787	14.03	0.781	19.10	0.735
YOLY [26]	15.72	0.714	14.71	0.748	13.16	0.762	16.28	0.717
USID-Net [27]	21.50	0.784	19.81	0.771	17.91	0.769	20.72	0.726
RefineDNet [56]	24.41	0.840	21.65	0.783	19.75	0.793	21.03	0.747
D^4 [53]	24.75	0.832	23.84	0.805	21.32	0.826	21.59	0.782
CUT [32]	24.22	0.815	23.51	0.827	22.90	0.804	21.26	0.766
Santa [51]	24.55	0.828	23.65	0.797	21.93	0.838	21.80	0.778
UNSB [22]	24.68	0.837	24.52	0.812	22.75	0.822	22.11	0.785
ODCR [47]	24.89	0.848	24.08	0.818	23.42	0.832	22.73	0.791
DN [18]	24.72	0.845	24.63	0.824	23.58	0.844	23.20	0.796
DDSB (ours)	**25.41**	**0.870**	**25.75**	**0.831**	**25.38**	**0.865**	**25.22**	**0.804**

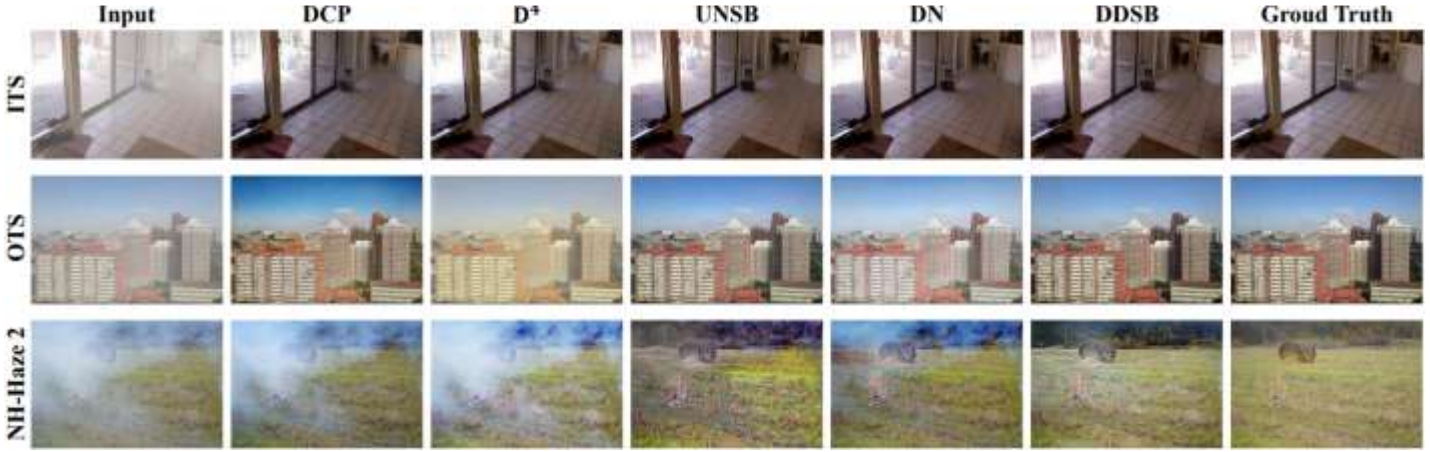


Experiment

- Experiment 2: Unpaired Dehazing

Table 3: Quantitative comparison of DDSB with the state-of-the-art unpaired dehazing methods on the generalized dehazing task, trained on SOTS-indoor, and the test result are shown. Cells where results are not available are replaced by "-". The time is measured on images of the size of 512×512 pixels using a single GPU.

Method	SOTS-indoor [25]		SOTS-outdoor [25]		NH-HAZE 2 [1]		Overhead	
	PSNR (dB)	SSIM	PSNR (dB)	SSIM	PSNR (dB)	SSIM	Para. (M)	Time (ms)
DCP [16]	13.10	0.699	19.13	0.815	14.90	0.668	-	-
CycleGAN [59]	21.34	0.898	20.55	0.856	13.95	0.689	11.38	10.22
YOLY [26]	15.84	0.819	14.75	0.857	13.38	0.595	32.00	-
USID-Net [27]	21.41	0.894	23.89	0.919	15.62	0.740	3.780	31.01
RefineDNet [56]	24.36	0.939	19.84	0.853	14.20	0.754	65.80	248.5
D^4 [53]	25.42	0.932	25.83	0.956	14.52	0.709	10.70	28.08
CUT [32]	24.30	0.911	23.67	0.904	15.92	0.758	11.38	10.06
Santa [51]	25.01	0.923	24.21	0.945	16.02	0.749	11.43	136
UNSB [22]	25.68	0.930	25.30	0.954	16.10	0.753	14.42	0.212
ODCR [47]	26.32	0.945	26.16	0.960	17.56	0.766	11.38	10.14
DN [18]	26.25	0.947	26.18	0.962	17.15	0.769	11.40	87.7
DDSB (ours)	**27.85**	**0.956**	**27.67**	**0.971**	**17.92**	**0.783**	14.68	0.019



Thanks for your attention!