Depth-Centric Dehazing and Depth-Estimation from Real-World Hazy Driving Video

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Project Page

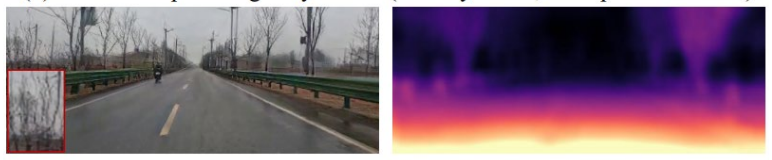
Motivation

- Obtaining clear RGB and accurate dense depth ground truth is challenging in real hazy scenes.
- Self-supervised depth estimation and physics-based dehazing are inherently complementary in real-world hazy scenes.

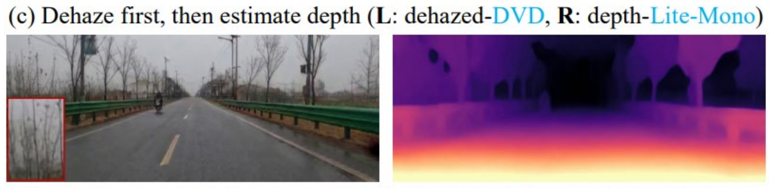
$$\begin{cases} I_t(x) = J_t(x)e^{-\beta d(x)} + A_\infty(1-e^{-\beta d(x)}) \\ J_t(x) = \mathcal{S}(J_s, y),\ y \sim KP_{x\to y}d(x)K^{-1}x \end{cases} \quad (1)$$

(a) **Misaligned** video frame pairs (**L**: hazy frame, **R**: matched clear reference)

(b) Estimate depth using hazy videos (**L**: hazy frame, **R**: depth-Lite-Mono)



(c) Dehaze first, then estimate depth (**L**: dehazed-DVD, **R**: depth-Lite-Mono)



(d) Simultaneously dehaze and estimate depth (**L**: dehazed, **R**: depth) (Ours)

Depth-Centric Learning (DCL)

Main idea:

- Based on Eq. (1), we propose a novel Depth-Centric Learning (DCL) framework to simultaneously remove haze and estimate depth from real-world hazy videos.
- We present two misaligned regularization discriminator networks, D_{MFIR} and D_{MDR}, for enhancing constraints on high-frequency details and weak texture regions.
- In real hazy scenes, scattering does not always conform to an ideal model, as β depends not only on wavelength but also on the size and distribution of scattering particles (e.g., patchy haze). Therefore, we assume β to be a non-uniform variable.

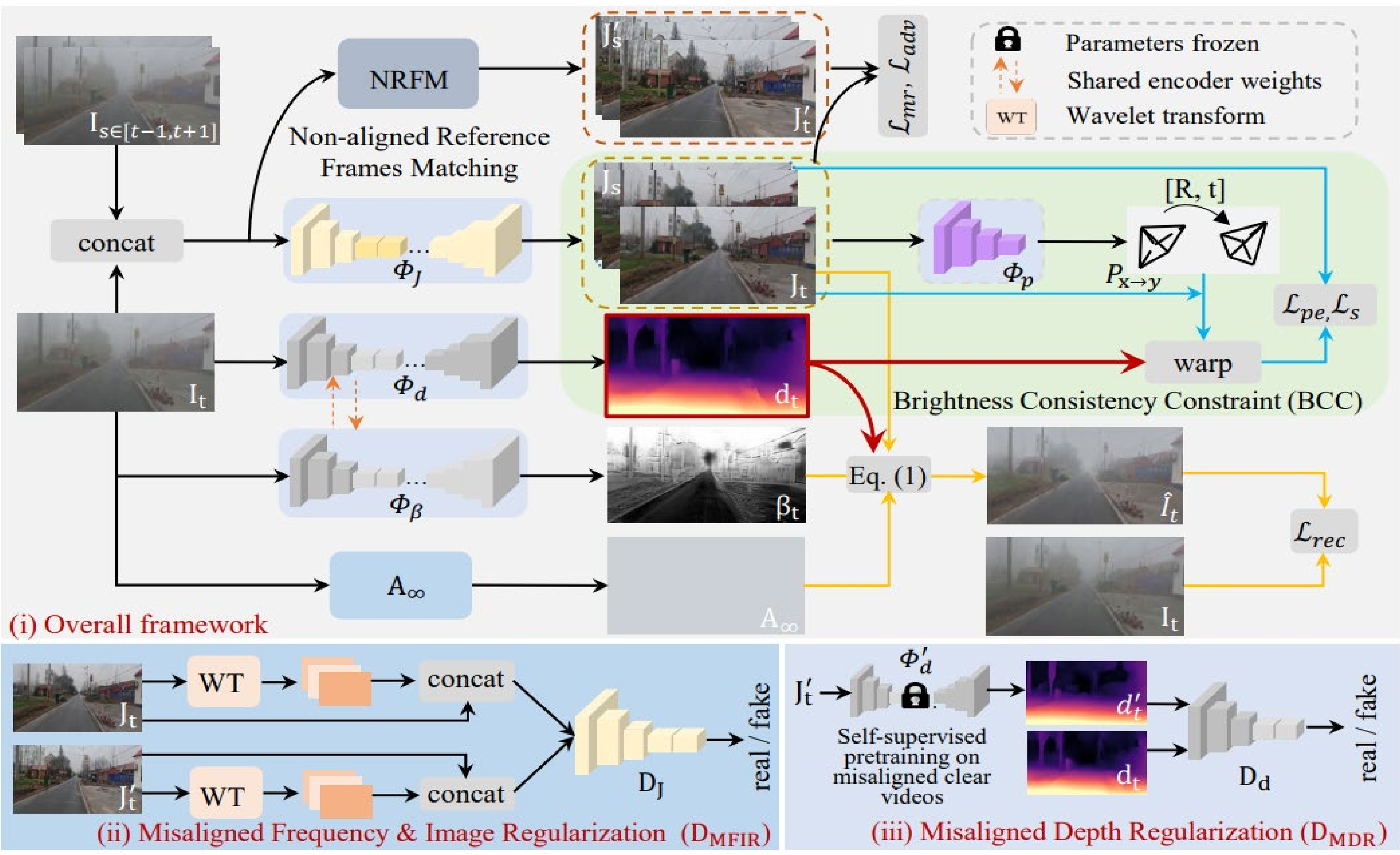
Train loss:

$$Loss = \overbrace{\boxed{\eta\mathcal{L}_{rec}}}^{\text{ASM Loss}} + \overbrace{(\gamma\mathcal{L}_{mr})}^{\text{Misaligned Reference Loss}} + \overbrace{\boxed{m_a\mathcal{L}_{pe} + \xi\mathcal{L}_s}}^{\text{BCC Loss}} + \overbrace{\boxed{\omega_1(\mathcal{L}_D^I + \mathcal{L}_G^I)}}^{D_{MFIR}} + \underbrace{\boxed{\omega_2\,(\mathcal{L}_D^d + \mathcal{L}_G^d)}}_{D_{MDR}}$$

Note: Based on the brightness consistency assumption, D_{MDR} regularizes the depth while also constraining the dehazing network to maintain brightness consistency across consecutive frames, thereby preventing flickering.

Overall Framework

Our DCL framework integrates the atmospheric scattering model (ASM) and brightness consistency constraint (BCC) via shared depth prediction. D_{MFIR} enhances high-frequency details in dehazed frames, while D_{MDR} reduces black holes in depth maps from weakly textured regions.



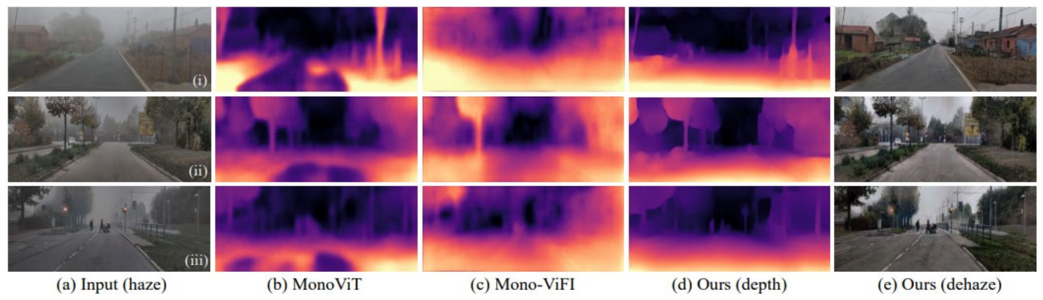
Experimental Results and Ablation Study

Quantitative dehazing results on three real hazy video datasets

Data Settings	Methods	Data Type	GoProHazy FADE ↓	GoProHazy NIQE ↓	DrivingHazy FADE ↓	DrivingHazy NIQE ↓	InternetHazy FADE ↓	InternetHazy NIQE ↓	Params (M)	FLOPs (G)	Inf. time (S)	Ref.
Unpaired	DCP	Image	1.0415	7.4165	1.1260	7.4455	0.9229	7.4899	-	-	1.39	CVPR'09
	RefineNet	Image	1.1454	6.1837	1.0223	6.5959	0.8535	6.7142	11.38	75.41	0.105	TIP'21
	CDD-GAN	Image	0.7797	6.0691	1.0072	6.1968	0.8166	6.1969	29.27	56.89	0.082	ECCV'22
	D^4	Image	1.5618	6.9302	0.9556	7.0448	0.6913	7.0754	**10.70**	**2.25**	0.078	CVPR'22
Paired	PSD	Image	0.9081	6.7996	0.9479	6.3381	0.8100	6.1401	33.11	182.5	0.084	CVPR'21
	RIDCP	Image	0.7250	5.2559	0.9187	5.3063	0.6564	5.4299	28.72	182.69	0.720	CVPR'23
	PM-Net	Video	0.7559	4.6274	1.0509	4.8447	0.7696	5.0182	151.20	5.22	0.277	ACMM'22
	MAP-Net	Video	0.7805	4.8189	1.0992	4.7564	1.0595	5.5213	28.80	8.21	0.668	CVPR'23
Non-aligned	NSDNet	Image	0.7197	6.1026	0.8670	6.3558	0.6595	4.3144	11.38	56.86	**0.075**	arXiv'23
	DVD	Video	0.7061	4.4473	0.7739	4.4820	0.6235	4.5758	15.37	73.12	0.488	CVPR'24
	DCL (Ours)	Video	**0.6914**	**3.4412**	**0.7380**	**3.5329**	**0.6203**	**3.5545**	11.38	56.86	**0.075**	-

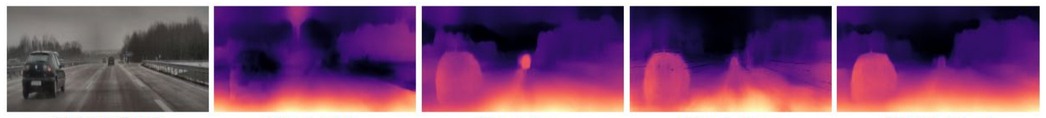
Quantitative depth estimation results on DENSE-Fog dataset

Method	DENSE-Fog (light) abs Rel↓	RMSE log↓	δ_1↑	δ_2↑	δ_3↑	DENSE-Fog (dense) abs Rel↓	RMSE log↓	δ_1↑	δ_2↑	δ_3↑	Params (M)	FLOPs (G)	Inf. time (S)	Ref.
MonoDepth2	0.418	0.475	0.499	0.735	0.847	1.045	0.632	0.530	0.771	0.864	14.3	8.0	**0.009**	ICCV'19
MonoViT	0.393	0.454	0.464	0.728	0.858	0.992	0.611	0.512	0.779	0.876	78.0	15.0	0.045	3DV'22
Lite-Mono	0.417	0.473	0.402	0.687	0.853	0.954	0.604	0.469	0.756	0.886	**3.1**	**5.1**	0.013	CVPR'23
RobustDepth	0.316	0.370	0.611	0.828	0.913	**0.605**	**0.515**	0.563	0.798	0.881	14.3	8.0	**0.009**	ICCV'23
Mono-ViFI	0.369	0.459	0.408	0.704	0.864	0.609	0.528	0.489	0.771	0.883	14.3	8.0	**0.009**	ECCV'24
DCL (Ours)	**0.311**	**0.364**	**0.623**	**0.839**	**0.920**	1.182	0.596	**0.612**	**0.829**	**0.900**	14.3	8.0	**0.009**	-



Ablation visualization of core module on DENSE-Fog (light)

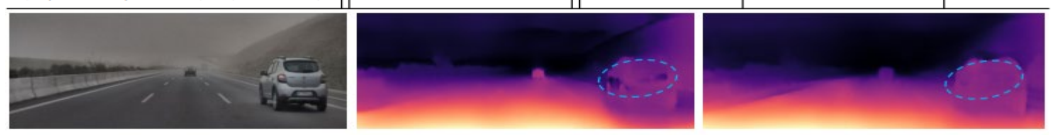
Method	BCC	D_{MFIR}	D_{MDR}	Abs Real↓	RMSE log↓	δ_1↑
DCL w/o BCC		✓	✓	0.636	0.569	0.439
DCL w/o D_{MFIR}	✓		✓	0.320	0.366	0.621
DCL w/o D_{MDR}	✓	✓		0.340	0.392	0.562
DCL (Ours)	✓	✓	✓	**0.311**	**0.364**	**0.623**



(a) Input (haze) (b) w/o BCC (c) w/o D_{MFIR} (d) w/o D_{MDR} (e) DCL (Ours)

Quantitative comparison different β types on DENSE-Fog (light)

Shape of β	Type	Abs Rel↓	RMSE log↓	δ_1↑
(1, 1, 1)	Constant	0.325	0.371	0.621
(1, 192, 640) (Ours)	Non-uniform	**0.311**	**0.364**	**0.623**



(a) Input (haze) (b) Constant β (depth) (c) Ours (depth)