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Project Page

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

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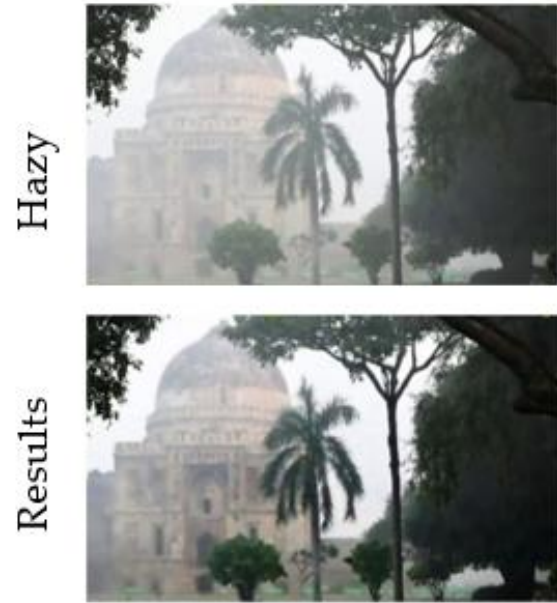


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Limitations of Existing Works



MAP-Net CVPR '23

Methods	Data Type	Inf. time (S)	Ref.
DCP	Image	1.39	CVPR'09
RefineNet	Image	0.105	TIP'21
CDD-GAN	Image	0.082	ECCV'22
D ⁴	Image	0.078	CVPR'22
PSD	Image	0.084	CVPR'21
RIDCP	Image	0.720	CVPR'23
PM-Net	Video	0.277	ACMM'22
MAP-Net	Video	0.668	CVPR'23
NSDNet	Image	0.075	arXiv'23
DVD	Video	0.488	CVPR'24

Inference time

L: MAP-Net dehazing results on real-world scenes, **R**: Inference time comparison.

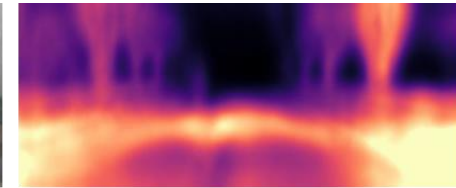
Motivation

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

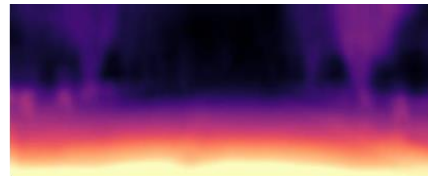
$$\begin{cases} I_t(x) = J_t(x)e^{-\beta \mathbf{d}(x)} + A_\infty(1 - e^{-\beta \mathbf{d}(x)}) \\ J_t(x) = \mathcal{S}(J_s, y), y \sim KP_{x \rightarrow y} \mathbf{d}(x) K^{-1}x \end{cases}$$



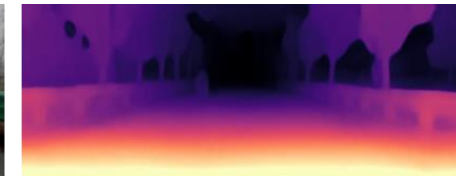
(a) **Misaligned** video frame pairs (L: hazy frame, R: matched clear reference)



(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)

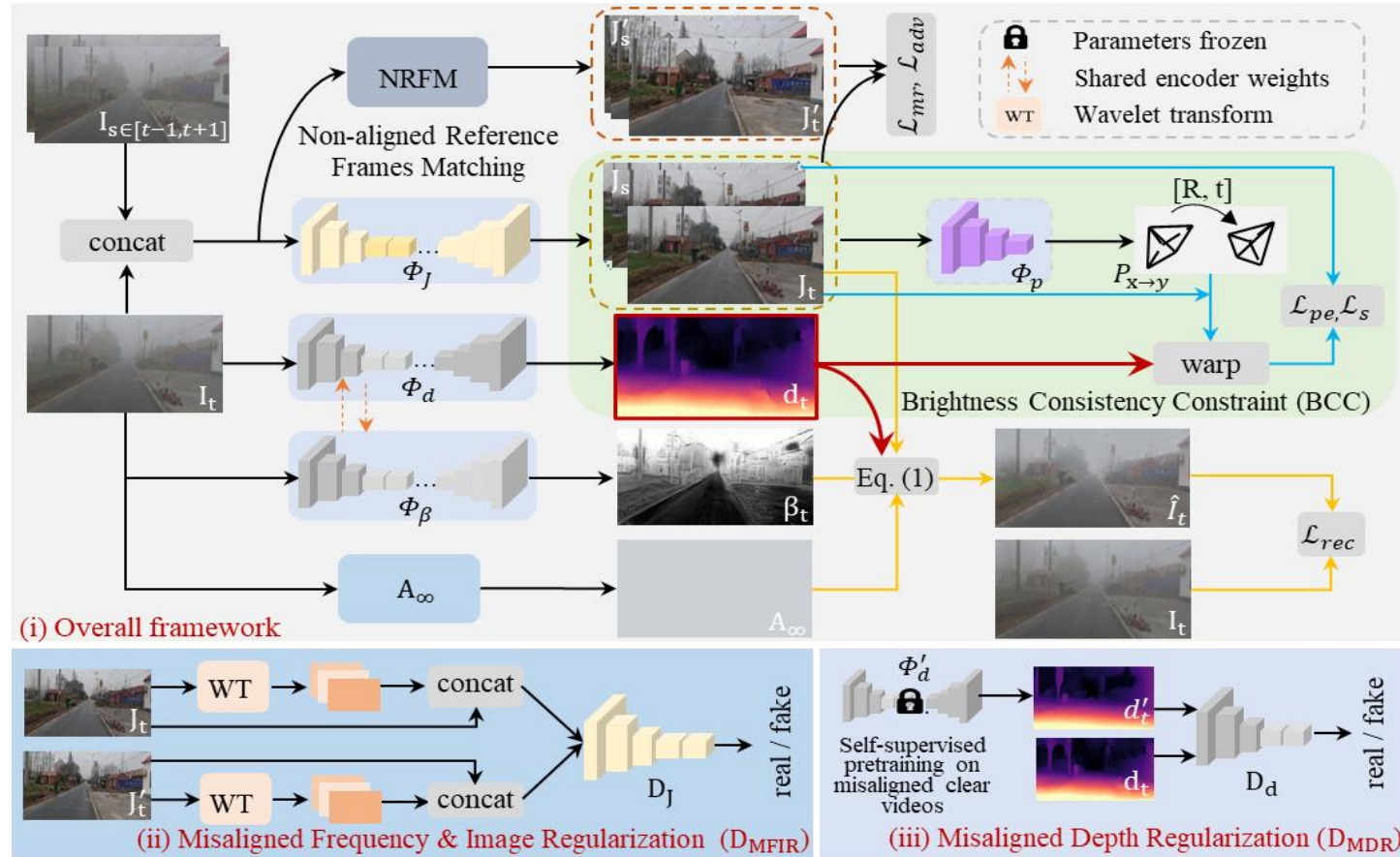


(d) Simultaneously dehaze and estimate depth (L: dehazed, R: depth) (**Ours**)

Comparison of different dehazing and depth estimation methods.

Depth-Centric Learning (DCL)

- We propose a novel Depth-Centric Learning (DCL) framework to simultaneously remove haze and estimate depth from real-world hazy videos.



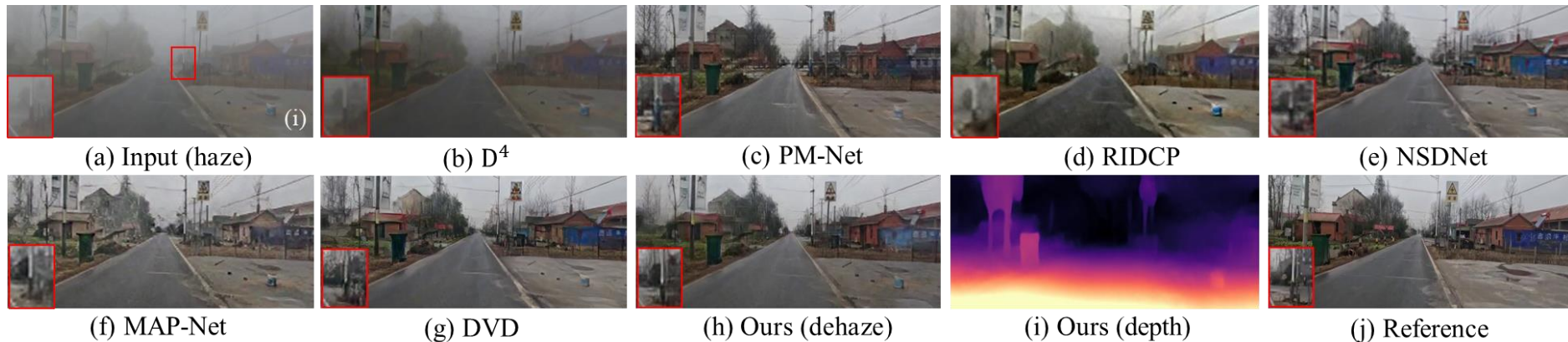
The pipeline of our Depth-Centric Learning (DCL) framework.

Quantitative Results

Quantitative dehazing results on three real hazy video datasets

Data Settings	Methods	Data Type	GoProHazy		DrivingHazy		InternetHazy		Params (M)	FLOPs (G)	Inf. time (S)	Ref.
			FADE ↓	NIQE ↓	FADE ↓	NIQE ↓	FADE ↓	NIQE ↓				
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	-

Comparisons of video dehazing performance on GoProHazy dataset

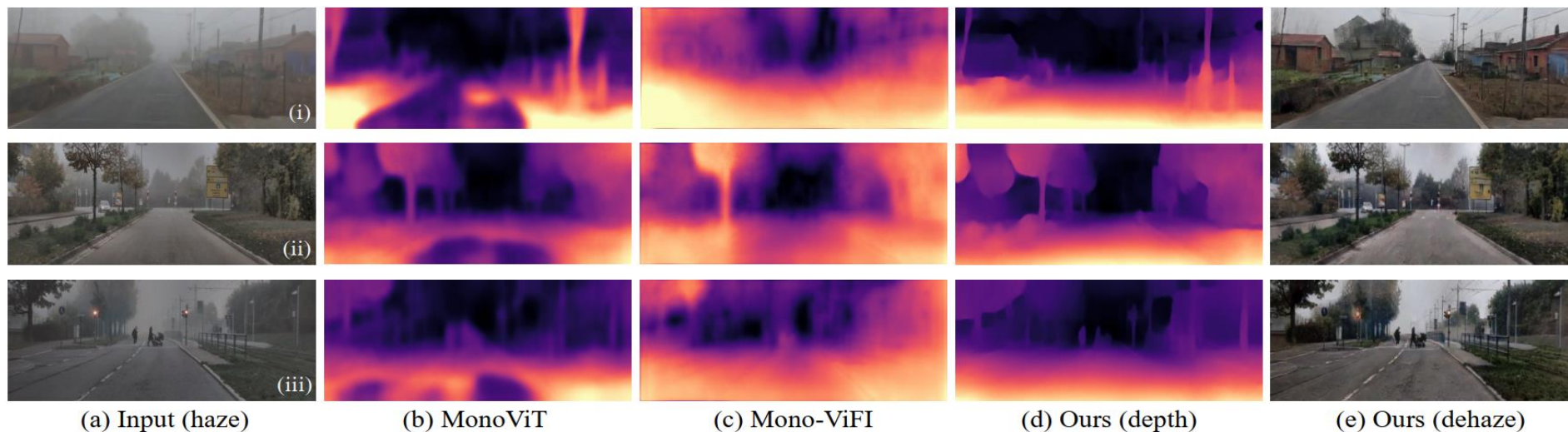


Quantitative Results

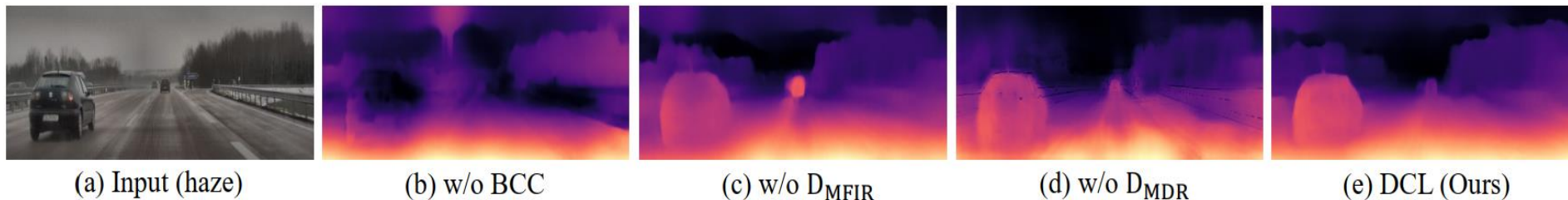
Quantitative depth estimation results on DENSE-Fog dataset

Method	DENSE-Fog (light)					DENSE-Fog (dense)					Params (M)	FLOPs (G)	Inf. time (S)	Ref.
	abs Rel↓	RMSE log↓	δ_1 ↑	δ_2 ↑	δ_3 ↑	abs Rel↓	RMSE log↓	δ_1 ↑	δ_2 ↑	δ_3 ↑				
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	-

Visual results on GoProHazy (i) and DENSE-Fog (ii-dense, iii-light).



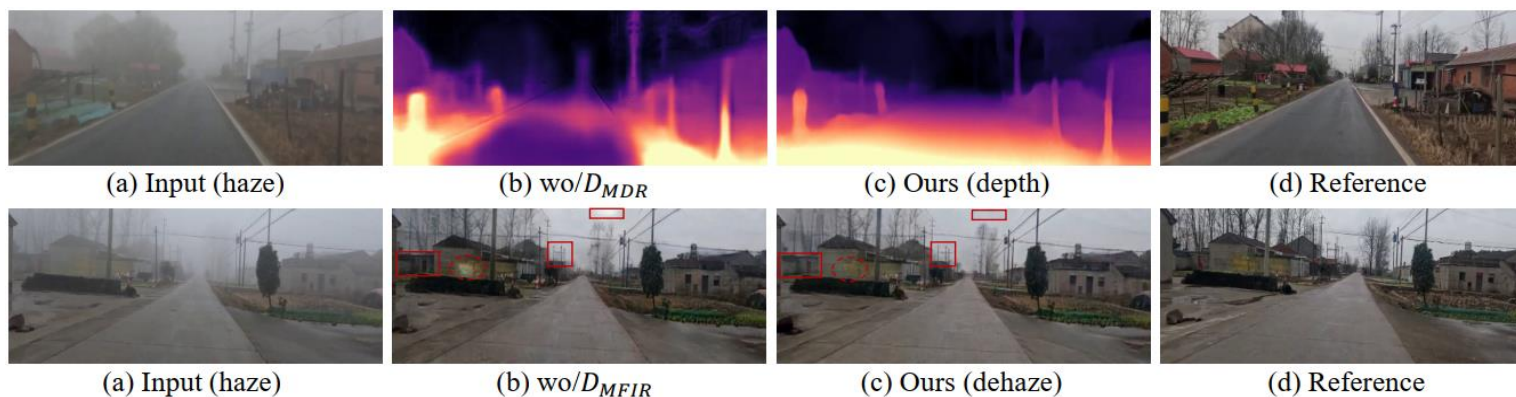
Ablation Study



Ablation visualization of BCC, D_{MFIR} and D_{MDR} 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

Ablation study on DENSE-Fog (light)



Ablation visualizations of D_{MFIR} and D_{MDR} are shown respectively on the depth and dehaze results from the GoProHazy dataset.

Ablation Study

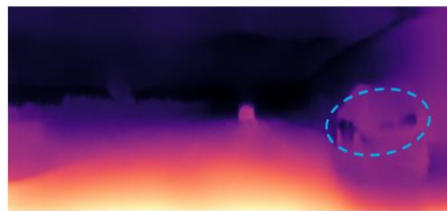
Method	\mathcal{L}_{pe}	\mathcal{L}_s	\mathcal{L}_{rec}	FADE↓	NIQE↓
DCL w/o \mathcal{L}_{pe}		✓	✓	0.6959	3.4785
DCL w/o \mathcal{L}_s	✓		✓	0.8163	3.5973
DCL w/o \mathcal{L}_{rec}	✓	✓		0.7581	3.7030
DCL (Ours)	✓	✓	✓	0.6914	3.4412

Ablation studies on different losses on GoProHazy

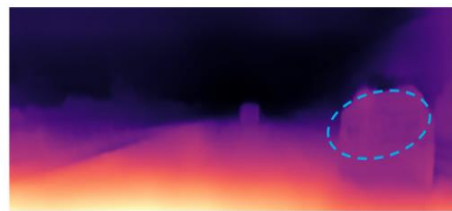
Shape of β	Type	Abs Rel↓	RMSE log↓	δ_1 ↑
(1, 1, 1)	Constant	0.325	0.371	0.621
(1, 192, 640) (Ours)	Non-uniform	0.311	0.364	0.623



(a) Input (haze)



(b) Constant β (depth)



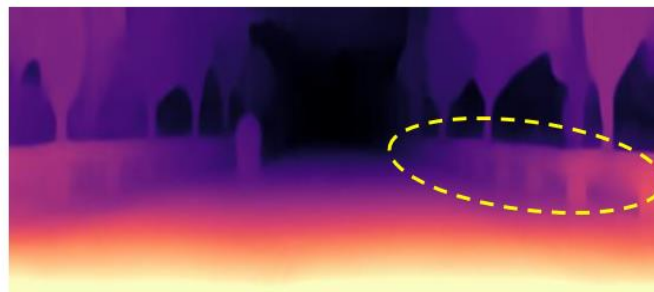
(c) Ours (depth)

Comparison of depth estimation across different β types on DENSE-Fog (light)

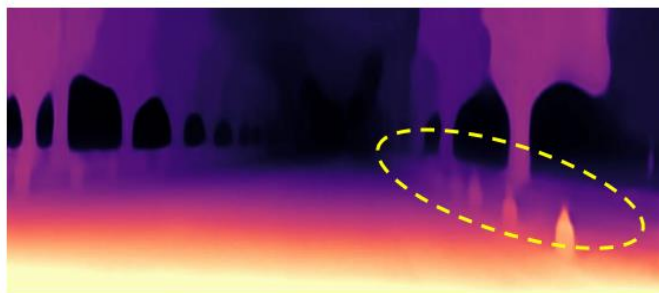
Discussion



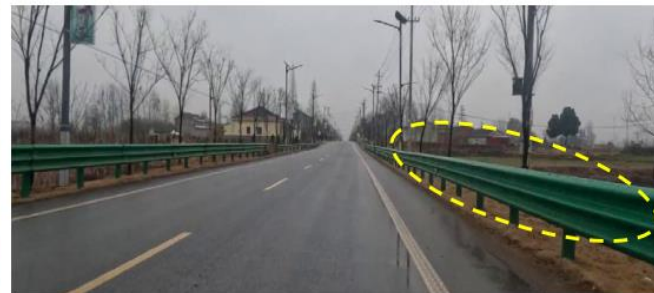
(a) Input (haze)



(b) Ours (depth)



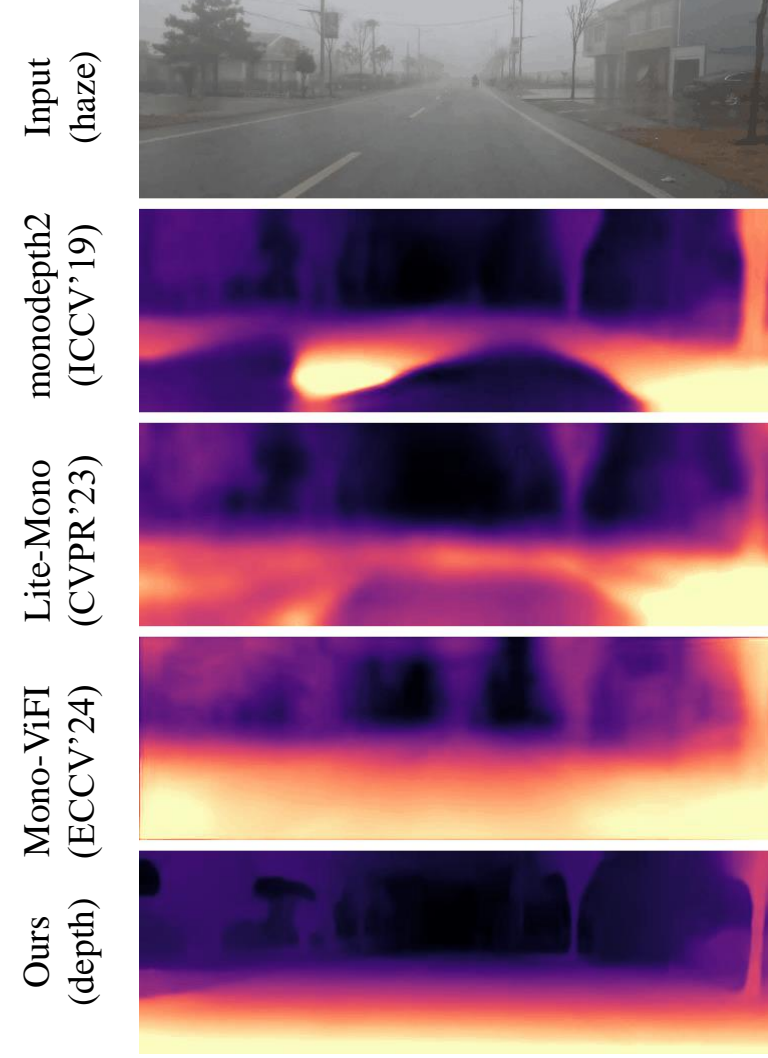
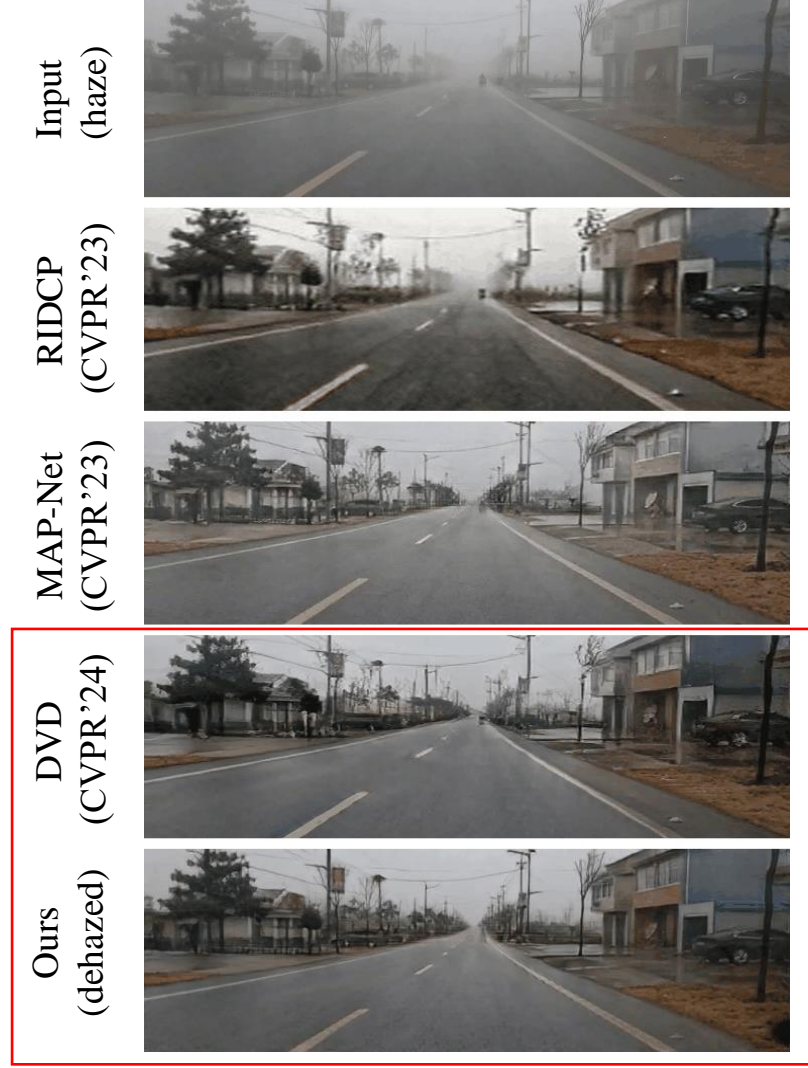
(c) Reference (depth)



(d) Reference (clear)

Visualizing the gains brought by ASM constraints
to depth estimation.

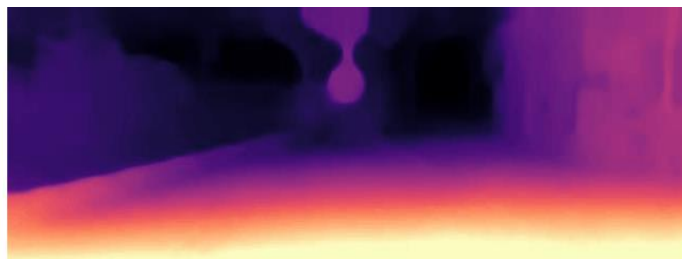
Video Demo



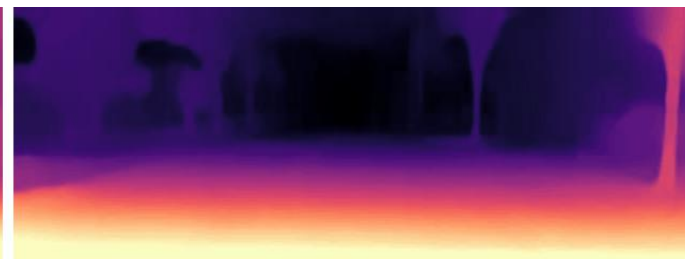
Video Demo



Input (haze)



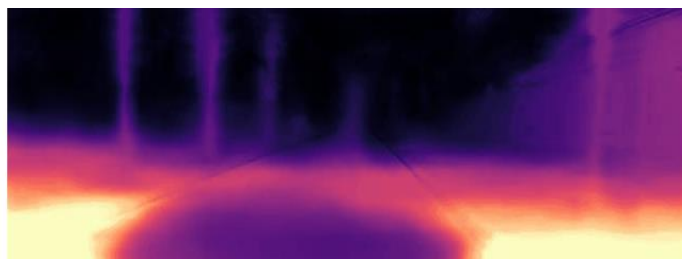
wo / BCC



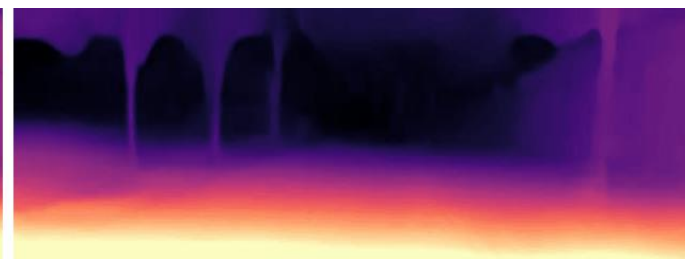
Ours (depth)



Input (haze)



wo / D_{MDR}



Ours (depth)



Input (haze)



wo / D_{MFIR}



Ours (dehaze)



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Thank you !



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Paper



Code



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