OneRestore: A Universal Restoration Framework for Composite Degradation

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Content

01 Introduction

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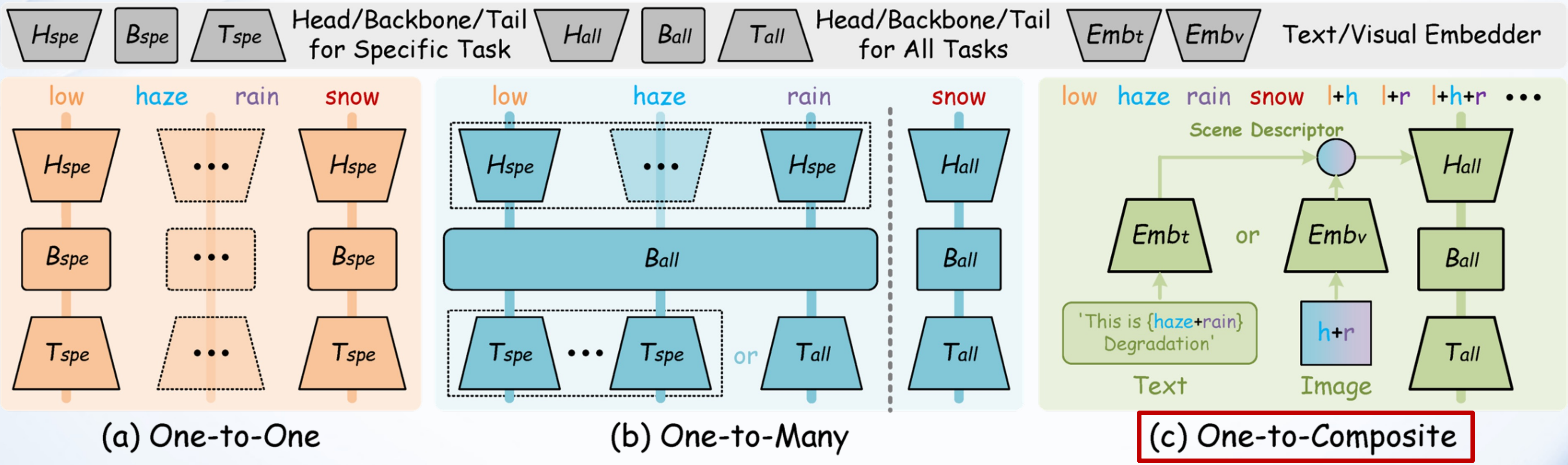
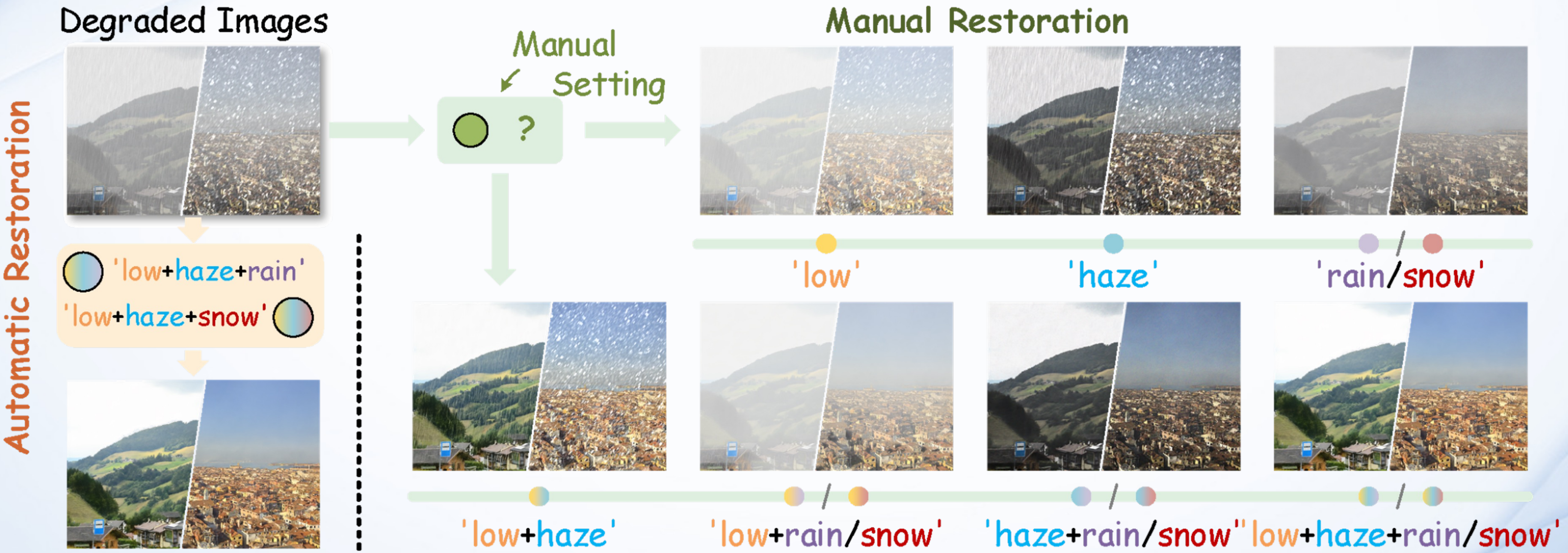


- **Adaptive Degradation Recognition**
- **Effective Multi-degradation Restoration with User Control**
- **Optimized Recovery for Clarity and Distinction**

01 Introduction



02 OneRestore: A Universal Restoration Framework

Composite Degradation Formulation

$$I(x) = \mathcal{P}_h(\mathcal{P}_{rs}(\mathcal{P}_l(J(x))))$$

Low-Light Conditions

$$I_l(x) = \mathcal{P}_l(J(x)) = \frac{J(x)}{L(x)} L(x)^{\gamma} + \varepsilon$$

Rain Streaks

$$I_{rs}(x) = \mathcal{P}_{rs}(I_l(x)) = I_l(x) + \mathcal{R}$$

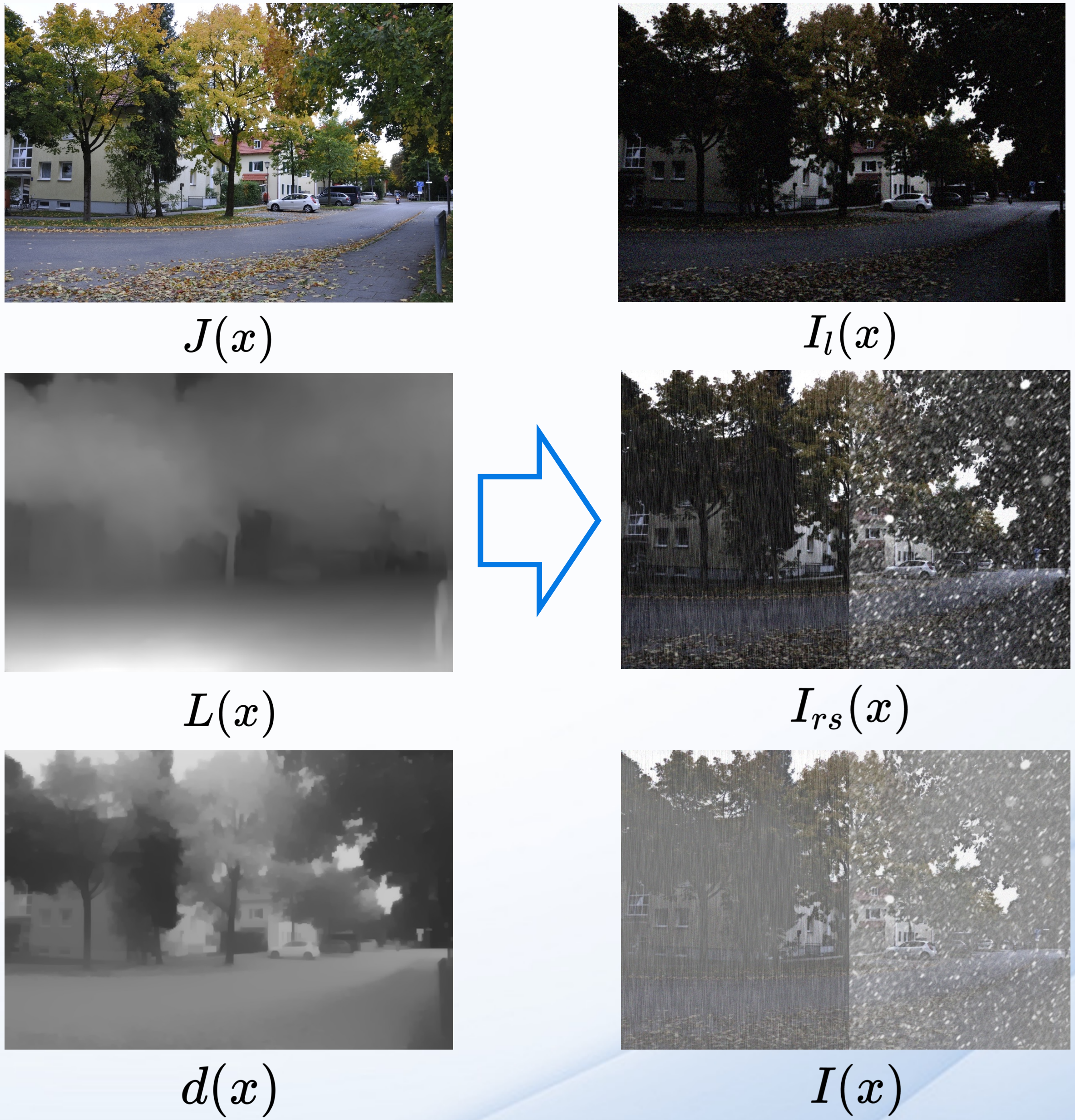
Snow Streaks

$$I_{rs}(x) = \mathcal{P}_{rs}(I_l(x)) = I_l(x)(1 - \mathcal{S}) + M(x)\mathcal{S}$$

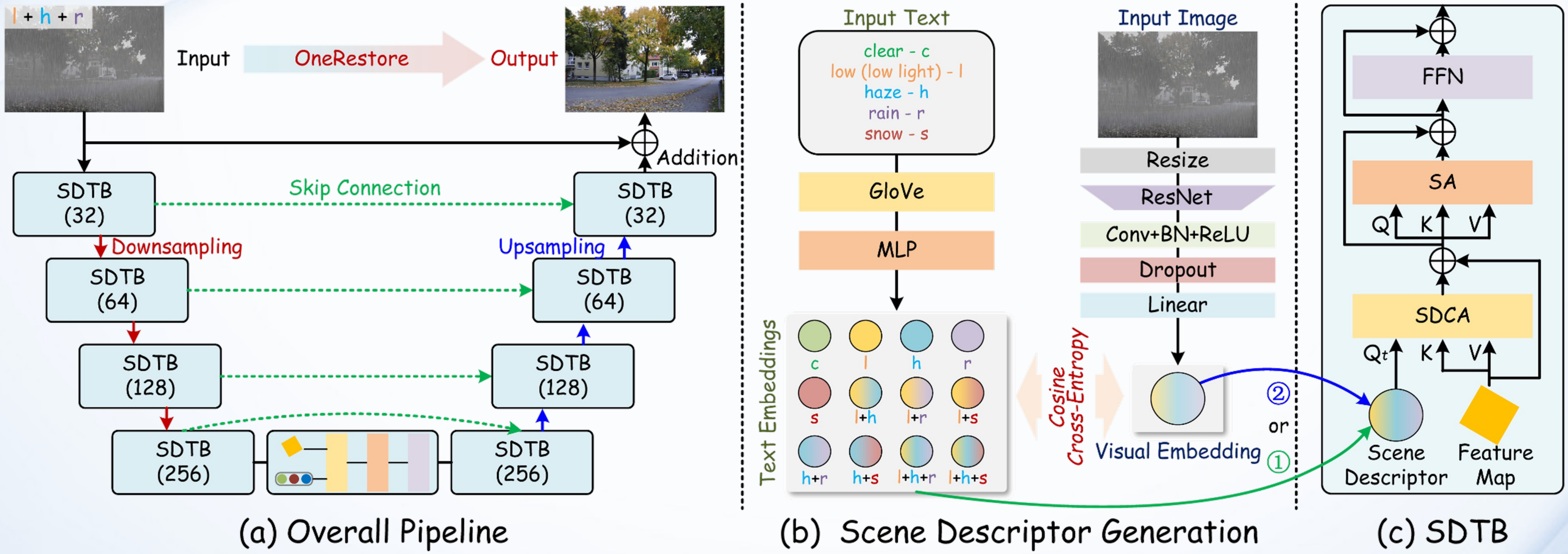
Haze Degradations

$$I(x) = \mathcal{P}_h(I_{rs}(x)) = I_{rs}(x)t + A(1 - t)$$

$$t = e^{-\beta d(x)}$$



OneRestore Architecture

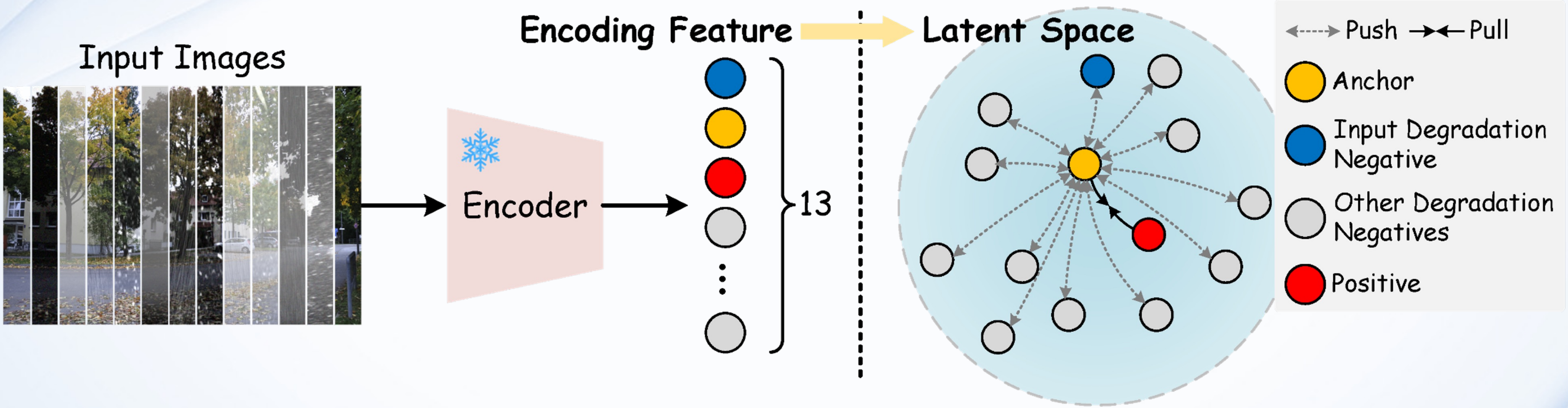


Our model allows versatile input scene descriptors, ranging from manual text embedding ① to visual attribute-based automatic extractions ②.

① Users input scene descriptions to create text embeddings.

② Visual attributes generate embeddings that approximate the best matching text.

Composite Degradation Restoration Loss



We enhance composite degradation restoration, introducing a unique loss for composite degradation that **leverages extra degraded images** as negative samples to reinforce model constraints.

Constraint Function:

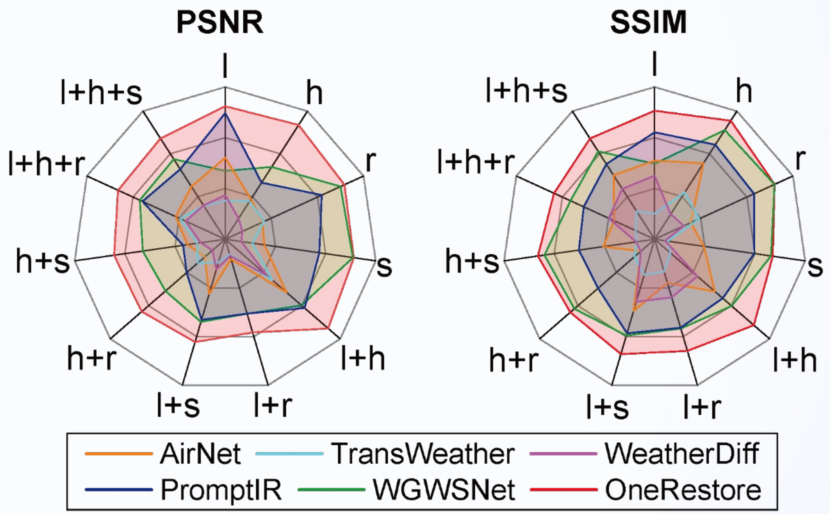
$$\mathcal{L}_c(J, \hat{J}, I, \{I_o\}) = \sum_{k=1}^{K} \xi_k \frac{\mathcal{L}_1(V_k(J), V_k(\hat{J}))}{\xi_c \mathcal{L}_1(V_k(\hat{J}), V_k(I)) + \sum_{o=1}^{O} \xi_o \mathcal{L}_1(V_k(I_o), V_k(\hat{J}))}$$

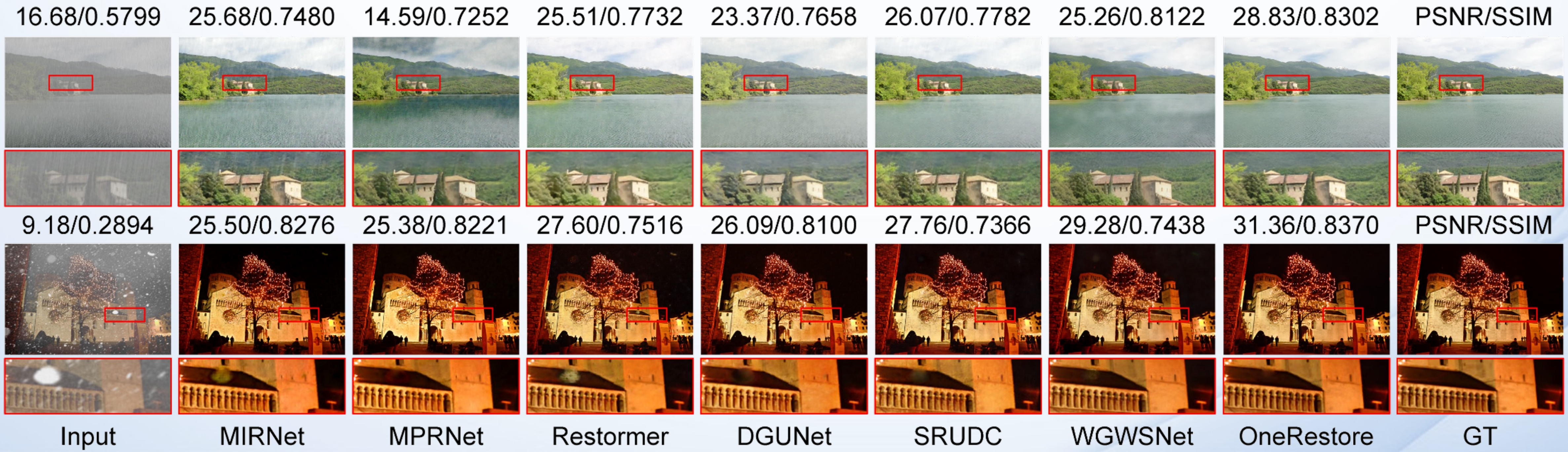
03 Experimental Evaluation

03 Experimental Evaluation

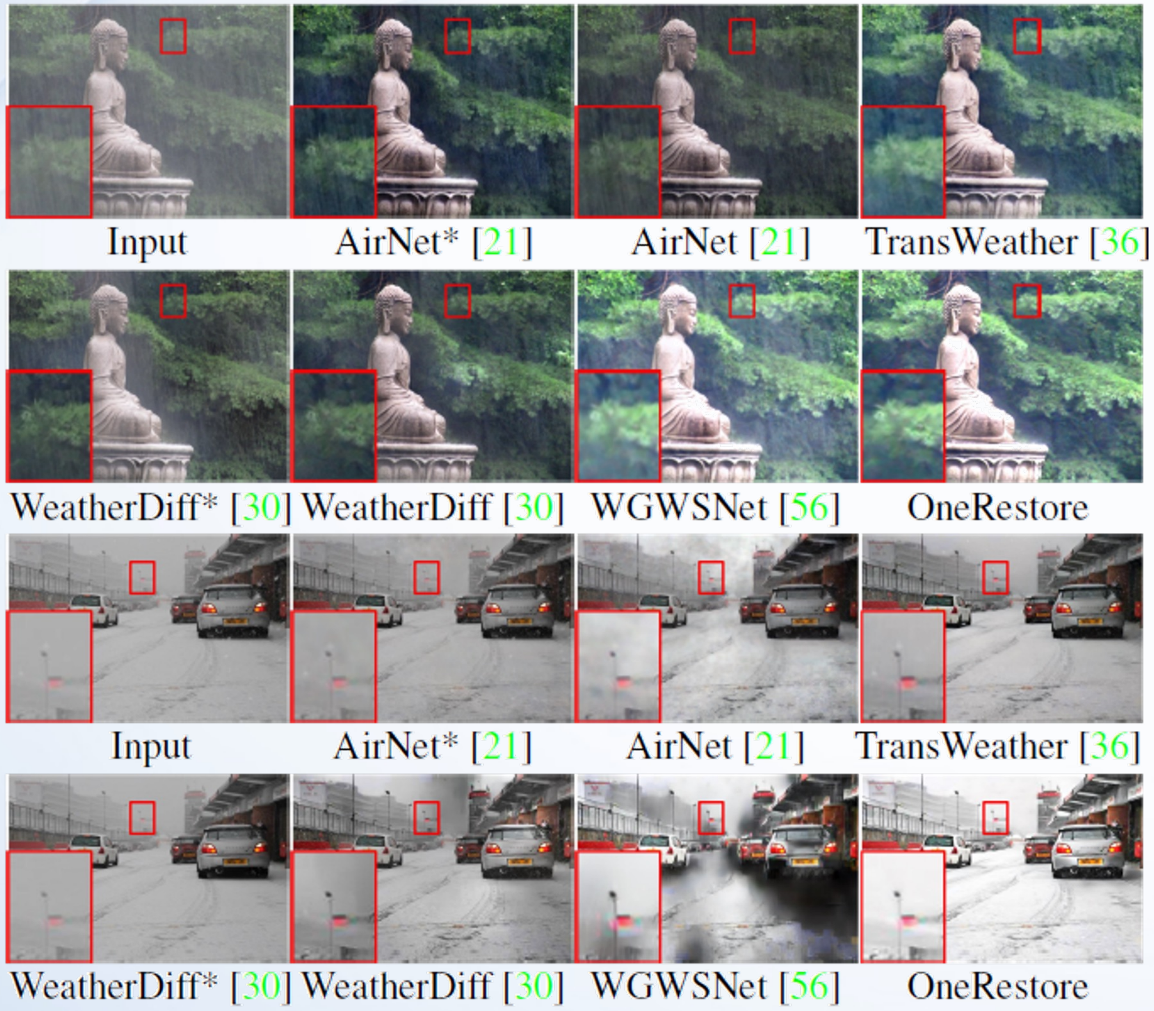
Synthesis Experiment

Types	Methods	Venue & Year	PSNR ↑	SSIM ↑	#Params
	Input		16.00	0.6008	-
One-to-One	MIRNet [86]	ECCV2020	25.97	0.8474	31.79M
	MPRNet [87]	CVPR2021	25.47	0.8555	15.74M
	MIRNetv2 [88]	TPAMI2022	25.37	0.8335	5.86M
	Restormer [85]	CVPR2022	26.99	0.8646	26.13M
	DGUNet [53]	CVPR2022	26.92	0.8559	17.33M
	NAFNet [7]	ECCV2022	24.13	0.7964	17.11M
	SRUDC [63]	ICCV2023	27.64	0.8600	6.80M
	Fourmer [95]	ICML2023	23.44	0.7885	0.55M
	OKNet [13]	AAAI2024	26.33	0.8605	4.72M
One-to-Many	AirNet [38]	CVPR2022	23.75	0.8140	8.93M
	TransWeather [65]	CVPR2022	23.13	0.7810	21.90M
	WeatherDiff [54]	TPAMI2023	22.49	0.7985	82.96M
	PromptIR [56]	NIPS2023	25.90	0.8499	38.45M
	WGWSNet [99]	CVPR2023	26.96	0.8626	25.76M
One-to-Composite	OneRestore		28.47	0.8784	5.98M
	OneRestore†		28.72	0.8821	5.98M





03 Experimental Evaluation



Multi-degradation Scene Restoration

Restoration Control by Text Description

03 Experimental Evaluation

Ablation for Model Configuration

SDCA	SA	FFN	PSNR ↑	SSIM ↑	Controllability
		✓	24.81	0.8607	
	✓	✓	27.19	0.8697	
✓		✓	27.93	0.8767	✓
✓	✓	✓	**28.72**	**0.8821**	✓

Scene Description Cross Attention (SDCA) improves performance and makes the model controllable.

Ablation for Loss Function

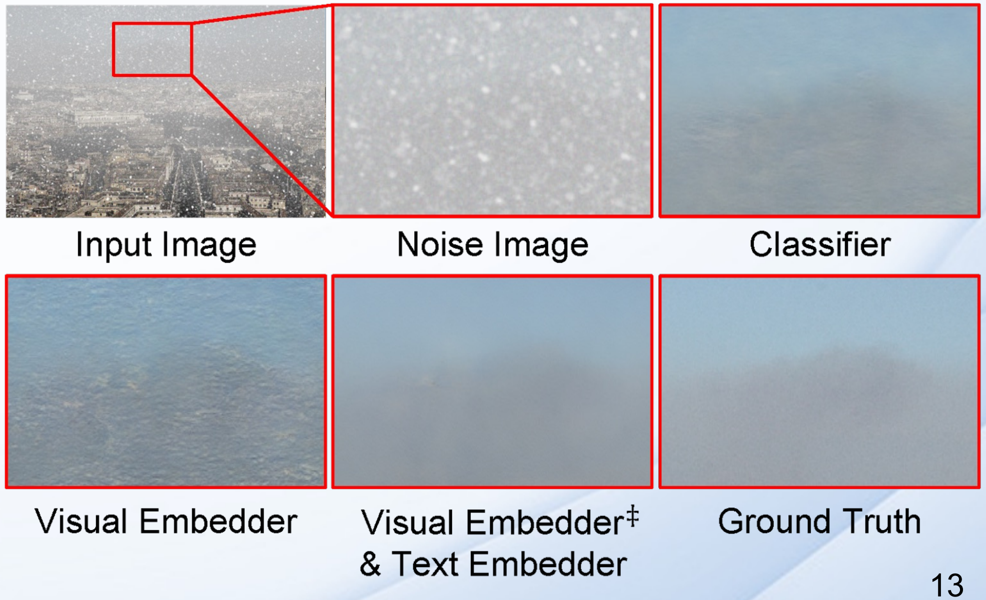
Smooth l_1	MS-SSIM	CL	CDRL	PSNR ↑	SSIM ↑
✓				28.16	0.8633
✓	✓			27.54	0.8708
✓	✓	✓		27.61	0.8723
✓	✓		✓	**28.72**	**0.8821**

Composite Degradation Restoration Loss (CDRL) demonstrates significantly better performance compared to standard contrastive loss (CL).

Ablation for Description Embedding Strategy

Models	PSNR ↑	SSIM ↑	Controllability
Classifier	28.19	0.8783	
Visual Embedder	28.24	0.8781	
Visual Embedder‡	28.47	0.8784	
Text Embedder	**28.72**	**0.8821**	✓

The proposed scene representation strategy enables more accurate identification of degradation, leading to the generation of more natural restoration results.



04 Conclusion

Contribution of our Work

- ◆ We introduce a unified imaging model that simulates multiple degradation types, forming the basis of our Composite Degradation Dataset.
- ◆ Our universal framework, using a cross-attention mechanism, enhances image restoration by integrating scene descriptors from text embeddings or visual attributes.
- ◆ Additionally, we develop a composite degradation restoration loss to improve the model's ability to distinguish between different degradations.

Code (Github)

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