Luminance-Aware Statistical Quantization: Unsupervised Hierarchical Learning for Illumination Enhancement

Author: Derong Kong[1], Zhixiong Yang[1], Shengxi Li[2], Shuaifeng Zhi[1], Li Liu[1], Zhen Liu[1], Jingyuan Xia[1,*]

Affiliation: [1]College of Electronic Science and Technology, National University of Defense Technology

[2]College of Electronic and Information Engineering, Beihang University

arXiv http://arxiv.org/abs/2511.01510

GitHub https://github.com/XYLGroup/LASQ

@ kongderong@nudt.edu.cn

Open Review https://openreview.net/forum?id=MoMXPzwVMb

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1. Background & Motivation

1. Pixel-mapping paradigms show poor cross-domain generalization.

Current LLIE models rely on deterministic pixel-wise mappings between paired low-/normal light data, making them heavily dataset-dependent, which neglects the continuous, hierarchical nature of real-world luminance transitions.

2. Physics priors are oversimplified and disconnected from learning.

Most gamma-based or Retinex-style priors apply uniform global corrections, failing to represent the power-law distributed and layered structure of natural illumination. So, learned models fit appearance-level brightness changes but not the underlying luminance statistics.

3. DM-based methods improve fidelity but lack adaptive luminance control.

Existing diffusion models simulate denoising from dark to bright without dynamic, hierarchical sampling of illumination layers. This prevents adaptive balancing between global consistency and local detail recovery, especially in unseen domains.

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1 Background & Motivation

2 Methodology

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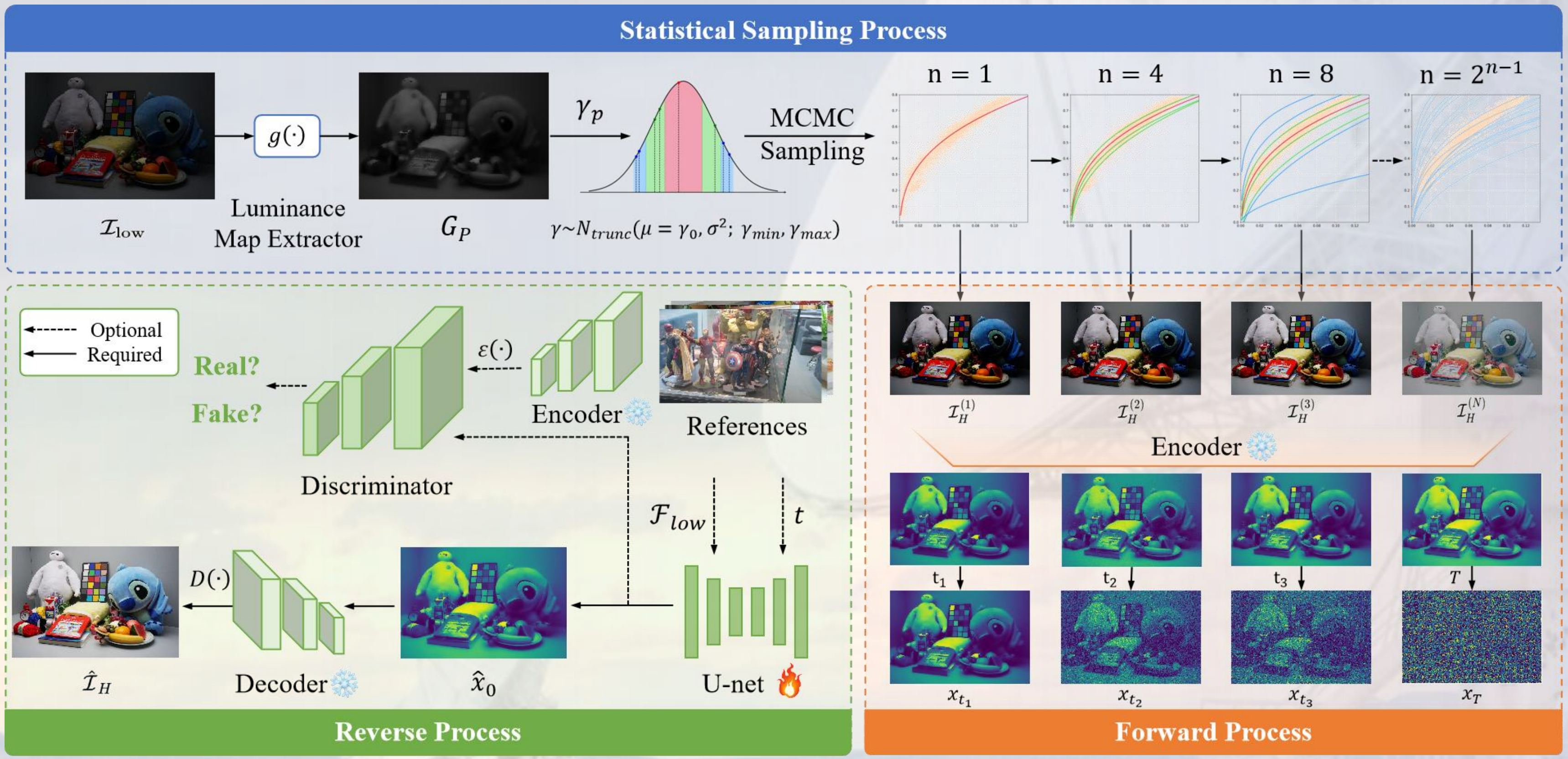
2. Methodology

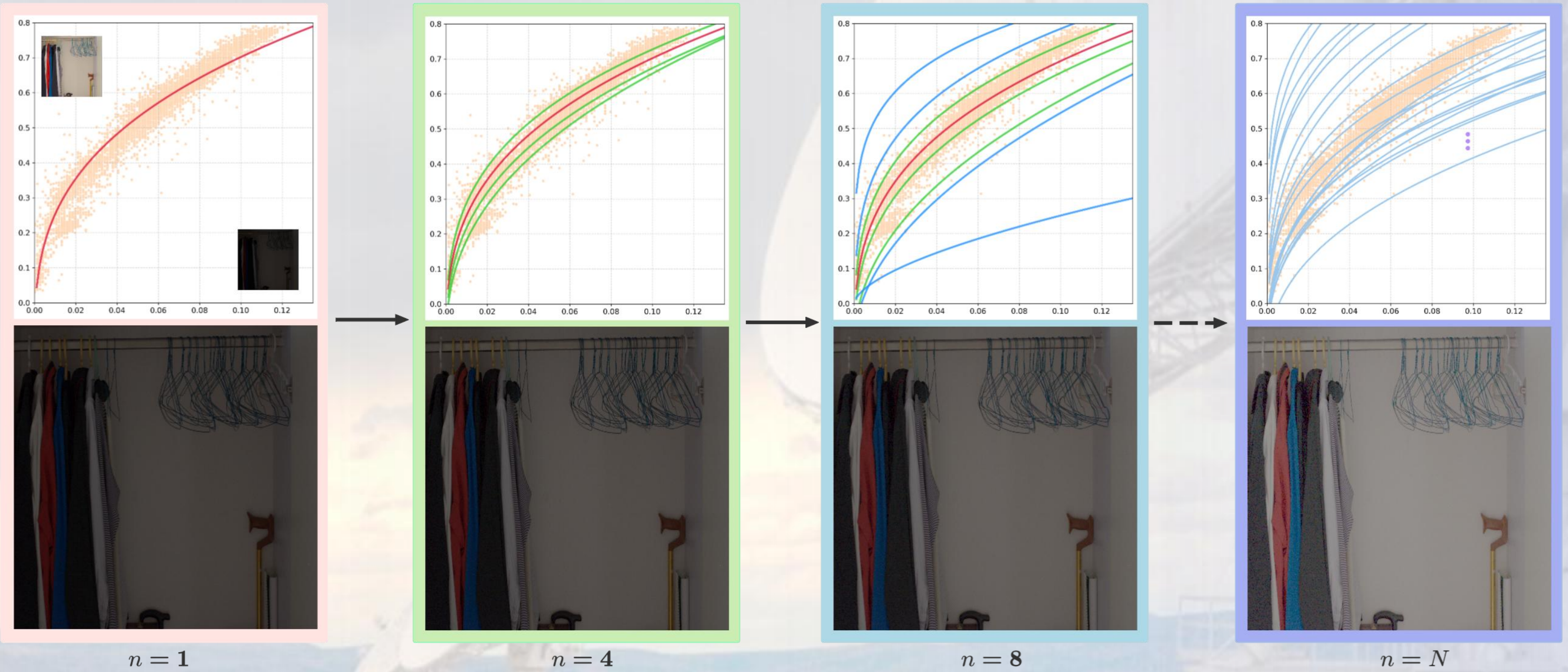
LASQ: An unsupervised low-light enhancement framework that eliminates dependency on reference images by modeling illumination as a hierarchical statistical process.



2. Methodology

1. A novel luminance variation coordinate system.

Redefines enhancement from pixel-level mapping to distribution-domain fitting, capturing the continuous power-law relationship between low- and normal-light luminance. This formulation makes the enhancement process physically grounded and less dataset-dependent.



2. Methodology

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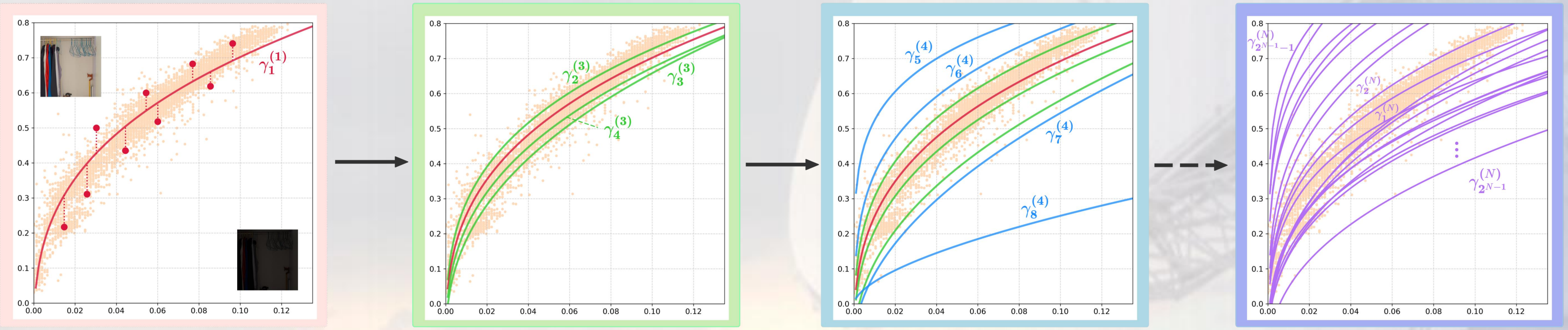
2. A dynamic sampling mechanism for luminance operators.

We introduce a hierarchical statistical sampling process that generates and refines luminance adaptation operators following power-law distributions. This sampling allows the model to statistically explore illumination operators instead of learning fixed mappings, achieving adaptive global-to-local control.



(a) $n = 1$ (b) $n = 3$ (c) $n = 4$ (d) $n = N$

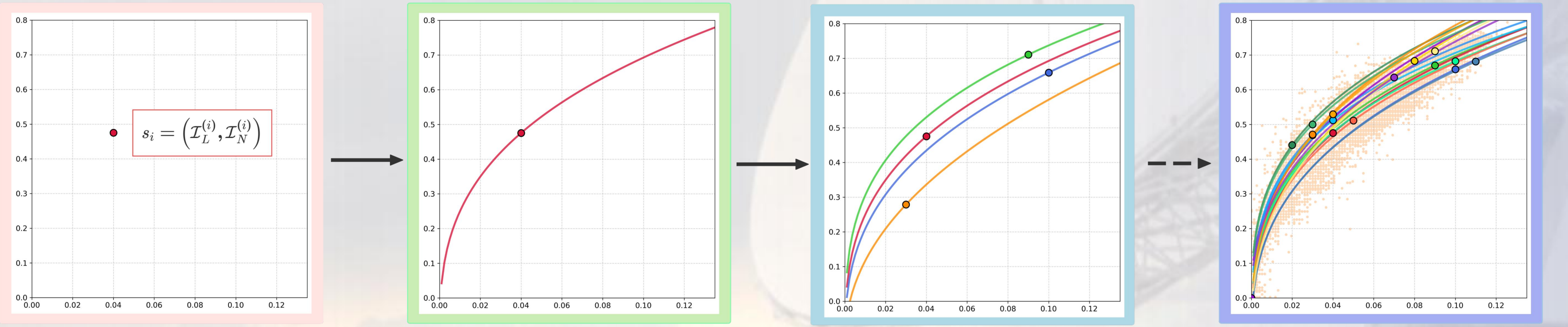
Luminance Adaptation Operator: $\gamma_P = (\alpha + G_P)^{\beta_P},\ \beta_P = 2G_P - 1 + \eta \frac{\sigma_{G_P}^2}{\sigma_{G_P}^2 + \delta}$

MCMC Process: $p\left(\mathcal{I}_H^{(n)}\right) = \int p(\mathcal{I}_H^{(n)} | \Gamma_n)\, p(\Gamma_n) d\Gamma_n \approx \sum_{z=1}^{2^n - 1} p(\mathcal{I}_H^{(n)} | \gamma_{P,z}^{(n)}) p(\gamma_{P,z}^{(n)})$

2. Methodology

3. A diffusion-driven framework with embedded sampling.

The sampled luminance operators are integrated into the diffusion forward process, guiding the model to traverse luminance layers in a coarse-to-fine, physics-aligned manner. This design enables hierarchical, reference-free illumination recovery while maintaining strong generalization across unseen domains.



(a) (b) (c) (d)

Forward Process: $q\left(x_t | x_0, \mathcal{F}_H^{(\psi(t))}\right) = \mathcal{N}(\sqrt{\bar{\alpha}_t} x_0 + \boxed{\sum_{s=1}^{t} \omega_{t,s} (\mathcal{F}_H^{(\psi(s))} - x_0)}, (1 - \bar{\alpha}_t) I)$

Hierarchical Guidance

Diffusion Denoising: $x_{t-1} = \frac{1}{\sqrt{1 - \beta_t}} (x_t - \beta_t \epsilon_\theta(x_t, t, \mathcal{F}_L)) + \sigma_t b, b \sim \mathcal{N}(0, I)$

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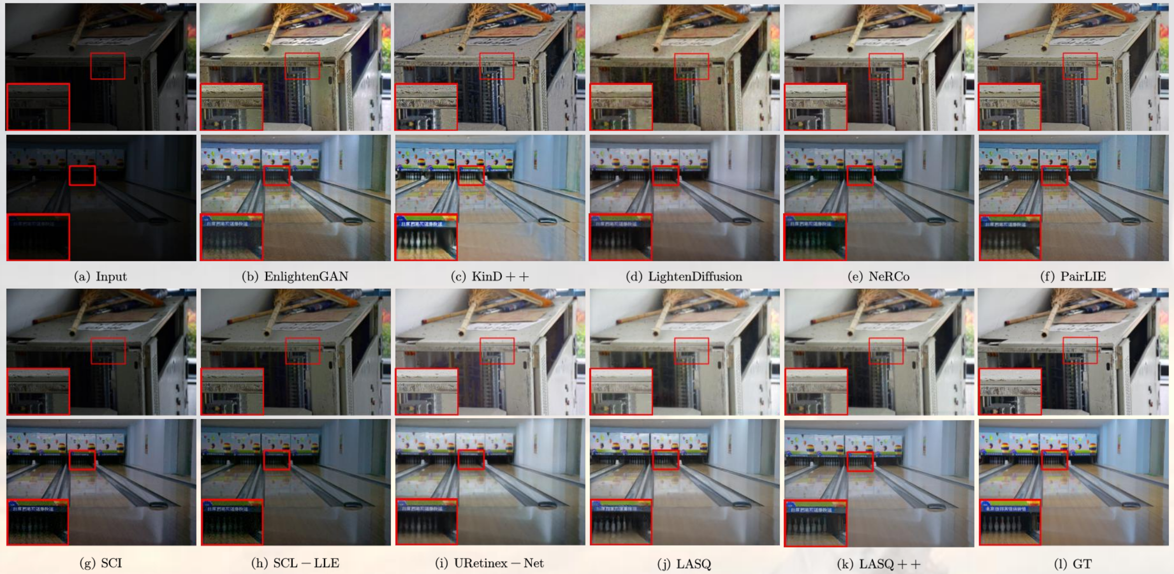
3. Experiments & Results

1. Visual Comparisons

LASQ delivers natural brightness restoration and fine structural fidelity comparable to supervised methods, while maintaining robust color consistency across domains. Unlike existing approaches that suffer from underexposure, overexposure, or artifacts, LASQ achieves clean, balanced illumination and superior generalization in both laboratory and real-world scenes.



Qualitative comparison on the LOLv1 and LSRW test sets

Qualitative comparison on the LIME and VV datasets

3. Experiments & Results

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2. Quantitative Results

Across diverse benchmarks, LASQ achieves state-of-the-art performance among unsupervised methods and matches leading supervised models on paired datasets. It maintains strong cross-scenario robustness without domain-specific tuning, confirming the effectiveness of its reference-free luminance modeling and diffusion-driven sampling.

Type	Method	LOLv1			LSRW			DICM		NPE		VV	
		PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	NIQE↓	PI↓	NIQE↓	PI↓	NIQE↓	PI↓
	RetinexNet	16.774	0.462	0.390	15.609	0.414	0.393	4.487	3.242	4.732	3.219	5.881	3.727
	KinD++	17.752	0.758	0.198	16.085	0.394	0.366	4.027	3.999	4.005	3.144	3.586	2.773
	LCDPNet	14.506	0.575	0.312	15.689	0.474	0.344	4.110	3.250	4.126	3.127	5.039	3.347
SL	URetinexNet	19.842	0.824	0.128	18.271	0.518	0.295	4.774	3.565	4.028	3.153	3.851	2.891
	SMG	23.814	0.809	0.144	17.579	0.538	0.456	6.224	4.228	5.300	3.627	5.752	3.757
	PyDiff	23.275	0.859	0.108	17.264	0.510	0.335	4.499	3.792	4.082	3.268	4.360	3.678
	Zero-DCE	14.861	0.562	0.330	15.867	0.443	0.315	3.951	3.149	3.826	2.918	5.080	3.307
	EnGAN	17.606	0.653	0.319	17.106	0.463	0.322	3.832	3.256	3.775	2.953	3.689	2.749
	SCI	14.784	0.525	0.333	15.242	0.419	0.321	4.519	3.700	4.124	3.534	5.312	3.648
	PairLIE	19.514	0.731	0.254	17.602	0.501	0.323	4.282	3.469	4.661	3.543	3.373	2.734
UL	SCL-LLE	10.754	0.506	0.382	13.110	0.310	0.396	5.129	3.809	4.873	3.692	5.513	4.316
	NeRCo	19.738	0.740	0.239	17.844	0.535	0.371	4.107	3.345	3.902	3.037	3.765	3.094
	LigDiff	20.453	0.803	0.192	18.555	0.539	0.311	3.724	3.144	3.618	2.879	2.941	2.558
	LASQ	20.375	0.814	0.191	18.137	0.547	0.308	3.715	3.128	3.571	2.764	2.777	2.623
	LASQ++	20.481	0.807	0.205	18.584	0.540	0.316	3.723	3.137	3.601	2.789	2.850	2.691

Quantitative comparison results of partial experiments

Type	Method	DICM		NPE		VV		LIME		MEF	
		NIQE↓	PI↓	NIQE↓	PI↓	NIQE↓	PI↓	NIQE↓	PI↓	NIQE↓	PI↓
	RetinexNet	4.487	3.242	4.732	3.219	5.881	3.727	4.802	3.522	4.152	3.411
	KinD++	4.027	3.999	4.005	3.144	3.586	2.773	4.035	3.217	3.874	3.285
	LCDPNet	4.110	3.250	4.126	3.127	5.039	3.347	4.128	3.332	3.912	3.398
SL	URetinexNet	4.774	3.565	4.028	3.153	3.851	2.891	3.987	3.104	3.721	3.185
	SMG	6.224	4.228	5.300	3.627	5.752	3.757	5.312	3.615	5.028	3.804
	PyDiff	4.499	3.792	4.082	3.268	4.360	3.678	4.412	3.685	4.228	3.572
	Zero-DCE	3.951	3.149	3.826	2.918	5.080	3.307	3.625	3.512	3.608	3.217
	EnlightenGAN	3.832	3.256	3.775	2.953	3.689	2.749	3.427	3.424	3.524	3.108
	SCI	4.519	3.700	4.124	3.534	5.312	3.648	4.032	3.518	3.892	3.415
	PairLIE	4.282	3.469	4.661	3.543	3.373	2.734	3.782	3.215	3.412	3.028
UL	SCL-LLE	5.129	3.809	4.873	3.692	5.513	4.316	5.104	4.302	4.872	4.115
	NeRCo	4.107	3.345	3.902	3.037	3.765	3.094	3.712	3.078	3.328	3.112
	LightenDiffusion	3.724	3.144	3.618	2.879	2.941	2.558	3.218	3.128	3.305	3.024
	LASQ	3.715	3.128	3.571	2.764	2.777	2.623	3.152	3.002	3.294	3.001
	LASQ++	3.723	3.137	3.601	2.789	2.850	2.691	3.167	3.046	3.309	3.013

Quantitative comparison results of additional experiments

3. Experiments & Results

3. Ablation Studies

Removing the adaptive luminance mechanism or reducing hierarchical depth significantly degrades performance. Static, fixed operators lead to poorer reconstruction fidelity, while limiting the hierarchy weakens smooth illumination transitions. These results verify that adaptive multi-scale luminance sampling is crucial for balancing global consistency, local detail, and cross-scenario generalization in LASQ.

(a) Input (b) FLA (c) LH (d) LASQ (e) LASQ++

Qualitative results of ablation studies

Method	LOLv1			LSRW			DICM		NPE		VV	
	PSNR↑	SSIM↑	LPIPS↓	PSNR↑	SSIM↑	LPIPS↓	NIQE↓	PI↓	NIQE↓	PI↓	NIQE↓	PI↓
FLA	16.741	0.715	0.273	15.490	0.508	0.399	4.265	3.529	3.937	3.114	3.683	3.007
LH	19.139	0.792	0.243	18.026	0.522	0.333	3.759	3.396	3.648	2.996	3.006	2.730
LASQ	20.375	0.814	0.191	18.137	0.547	0.308	3.715	3.128	3.571	2.764	2.777	2.623
LASQ++	20.481	0.807	0.205	18.584	0.540	0.316	3.723	3.137	3.601	2.789	2.850	2.691

Quantitative results of ablation studies

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Email: kongderong@nudt.edu.cn
yzx21@nudt.edu.cn
j.xia10@nudt.edu.cn

THANK YOU FOR LISTENING!