ECMamba: Consolidating Selective State Space Model with Retinex Guidance for Efficient Multiple Exposure Correction

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Motivation

Exposure correction is a challenging ill-posed problem:

- ❗ distinct optimization flows

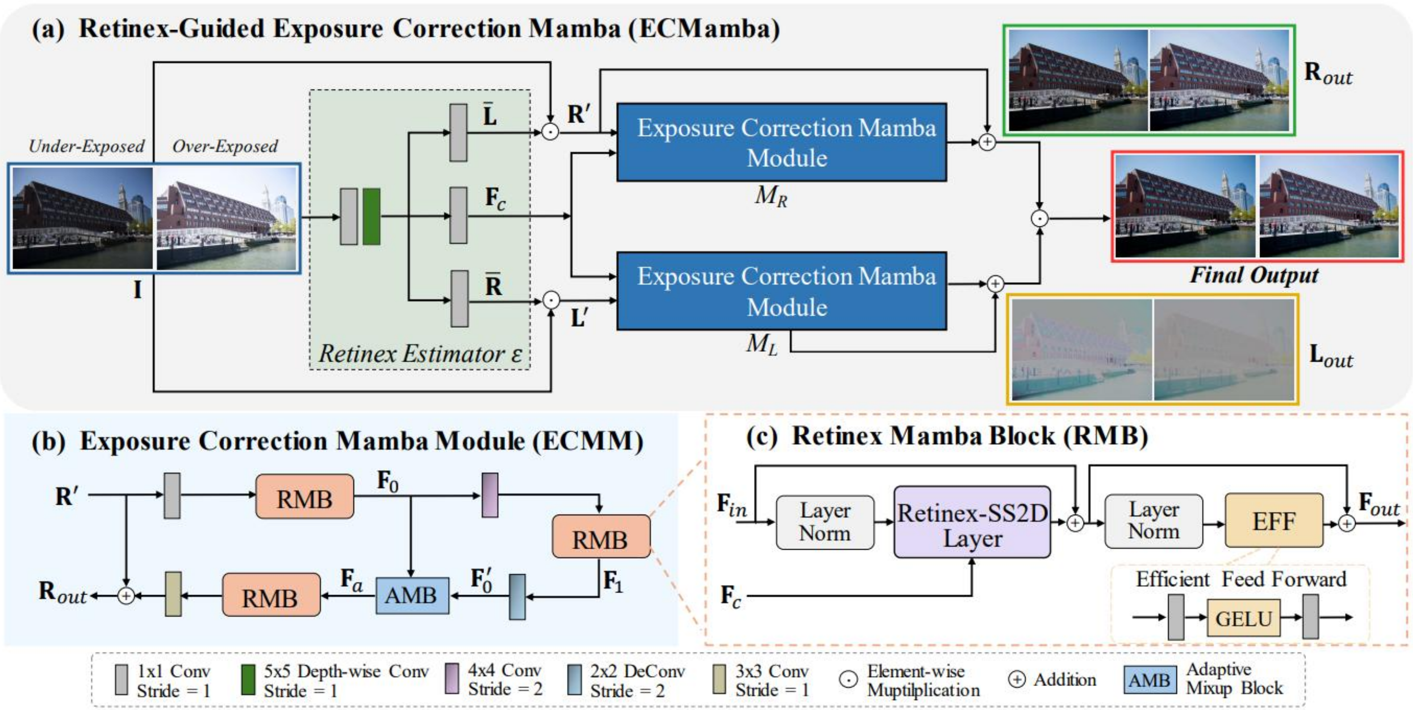
$$I_{over} \xrightarrow{f_\theta} \underbrace{I_{high}^1, I_{high}^2, \cdots, I_{high}^N}_{\text{multiple sub-optimal results}} \xleftarrow{f_\theta} I_{under}$$

- ❗ current methods struggle to decompose illumination and reflectance

- ❗ require strong models with good performance and high efficiency

Proposed Method

ECMamba Framework



- we propose ECMamba for exposure correction task

- two-branch retinex-guided framwork

$$(\bar{\mathbf{R}}, \bar{\mathbf{L}}, \mathbf{F}_c) = \mathcal{E}(\mathbf{I}_{LQ})$$

$$\mathbf{R}' = \mathbf{I}_{LQ} \odot \bar{\mathbf{L}}$$

$$\mathbf{L}' = \mathbf{I}_{LQ} \odot \bar{\mathbf{R}}$$

$$\mathbf{R}_{out} = \mathbf{R}' + \mathcal{M}_R(\mathbf{R}'; \mathbf{F}_c)$$

$$\mathbf{L}_{out} = \mathbf{L}' + \mathcal{M}_L(\mathbf{L}'; \mathbf{F}_c)$$

$$\mathbf{I}_{out} = \mathbf{R}_{out} \odot \mathbf{L}_{out}$$

$\mathcal{M}_R$, $\mathcal{M}_L$: restore the reflectance and illumination, respectively

Proposed Method

- $\mathcal{M}_R$ and $\mathcal{M}_L$ are designed based on Mamba

↓

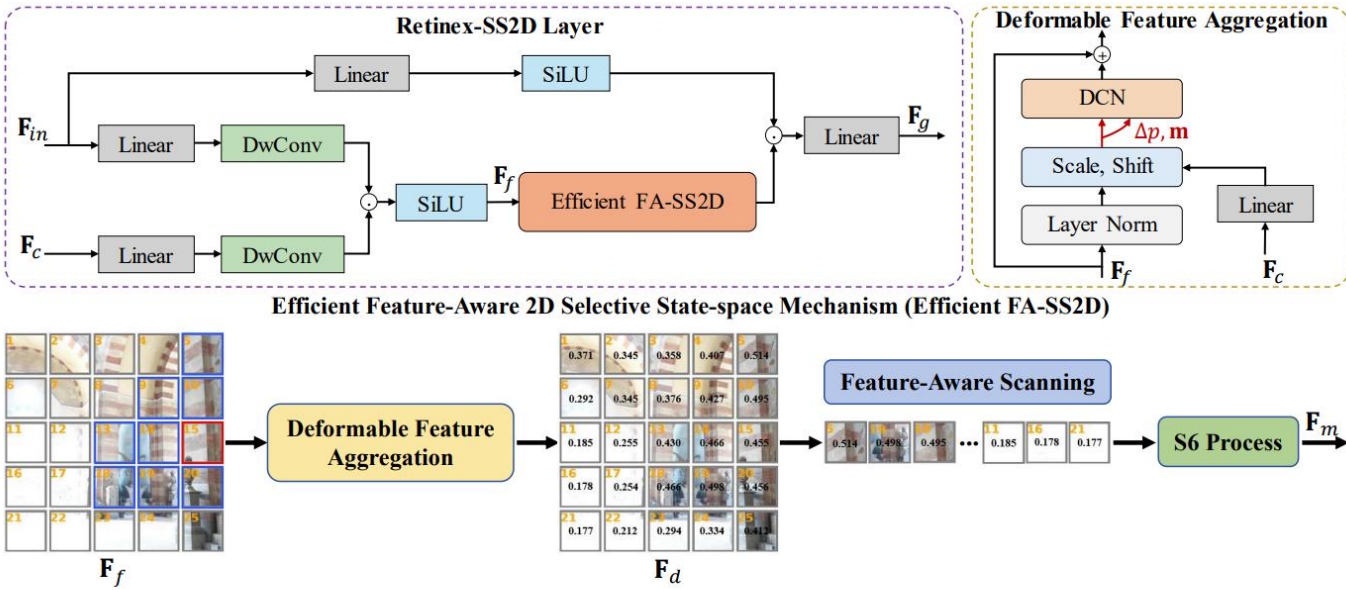
powerful modeling capability and high efficiency

To make Mamba better process vision data, especially under-/over-exposed images,

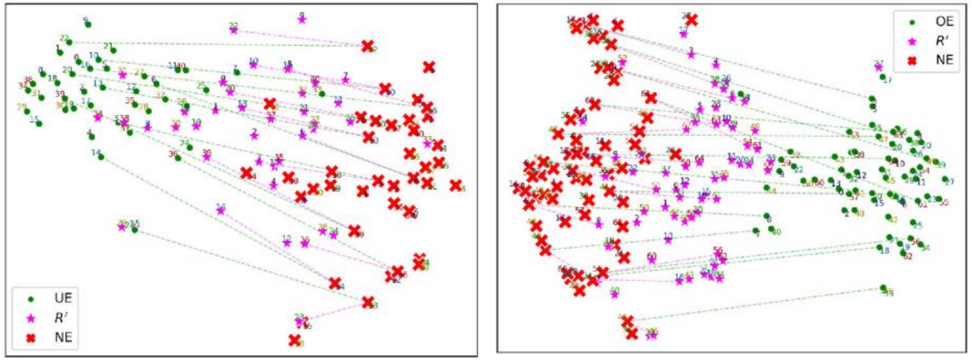
a new SS2D layer guided by the retinex information

a feature-aware scanning strategy based on deformable feature aggregation

Retinex-SS2D Layer

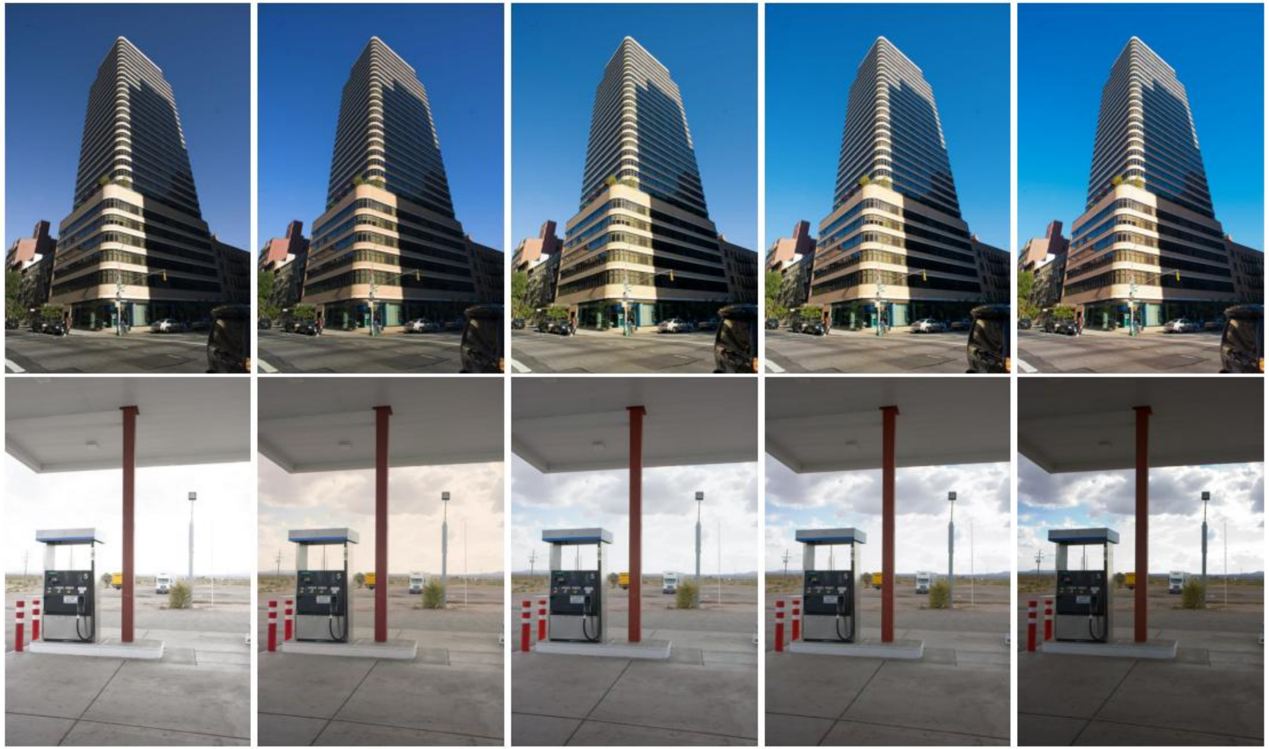


Observations within ECMamba



From Input $\longrightarrow \mathbf{R}' \longrightarrow \mathbf{R}_{out} \longrightarrow \mathbf{I}_{out}$

better color preservation and detail recovery, closer distance from NE Image



UE/OE Input | $\mathbf{R}'$ | $\mathbf{R}_{out}$ | $\mathbf{I}_{out}$ | NE Image

Experiment Results

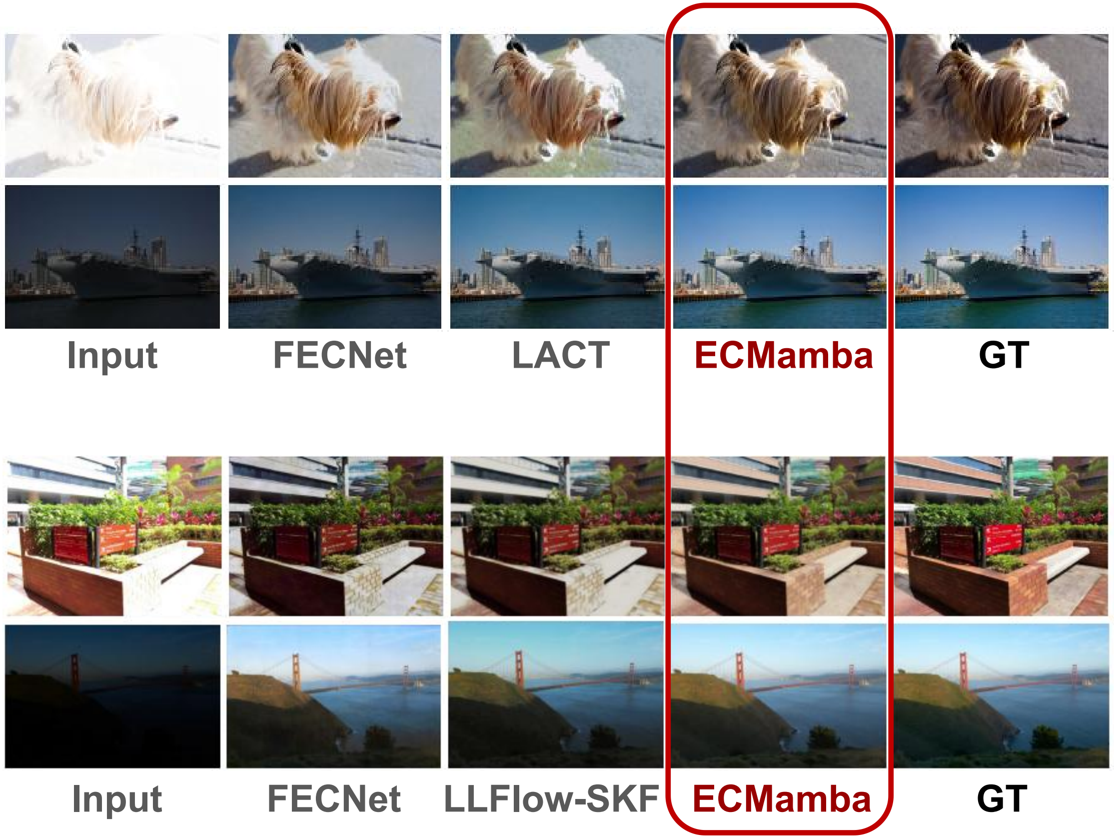
Results on ME and SICE Datasets

Methods	ME Dataset [1] Under-exposed PSNR↑	SSIM↑	Over-exposed PSNR↑	SSIM↑	Average PSNR↑	SSIM↑	SICE Dataset [5] Under-exposed PSNR↑	SSIM↑	Over-exposed PSNR↑	SSIM↑	Average PSNR↑	SSIM↑
ZeroDCE [16] CVPR'20	14.55	0.589	10.40	0.5142	12.06	0.544	16.92	0.633	7.11	0.429	12.02	0.531
RUAS [24] CVPR'21	13.43	0.681	6.39	0.466	9.20	0.552	16.63	0.559	4.54	0.320	10.59	0.439
URetinexNet [37] CVPR'22	13.85	0.737	9.81	0.673	11.42	0.699	17.39	0.645	7.40	0.454	12.40	0.550
KinD [44] MM'19	15.51	0.761	11.66	0.730	13.20	0.742	13.43	0.484	7.85	0.478	10.64	0.481
LLFlow* [34] AAAI'22	22.35	0.858	22.46	0.863	22.42	0.861	21.45	0.679	20.29	0.671	20.87	0.675
LLFLow-SKF* [38] CVPR'23	22.58	0.859	22.72	0.865	22.66	0.863	21.61	0.671	20.55	0.695	21.08	0.683
DRBN [40] CVPR'20	19.74	0.829	19.37	0.832	19.52	0.831	17.96	0.677	17.33	0.683	17.65	0.680
DRBN+ERL [21] CVPR'23	19.91	0.831	19.60	0.838	19.73	0.836	18.09	0.674	17.93	0.687	18.01	0.680
FECNet [20] ECCV'22	22.96	0.860	23.22	0.875	23.12	0.869	22.01	0.674	19.91	0.696	20.96	0.685
FECNet+ERL [21] CVPR'23	23.10	0.864	23.18	0.876	23.15	0.871	22.35	0.667	20.10	0.689	21.22	0.678
Retiformer* [6]ICCV'23	22.77	0.862	22.24	0.860	22.45	0.861	22.15	0.665	20.21	0.669	21.18	0.667
LACT [4] ICCV'23	23.49	0.862	23.68	0.872	23.57	0.869	-	-	-	-	-	-
Ours	**23.64**	**0.875**	**23.84**	**0.882**	**23.76**	**0.879**	**22.87**	**0.745**	**21.23**	**0.727**	**22.05**	**0.736**

Results on LOL-series Datasets

Methods	LOLv1 [36] PSNR↑	SSIM↑	LOLv2-real [41] PSNR↑	SSIM↑	LOLv2-synthetic [41] PSNR↑	SSIM↑
Zero-DCE [16] CVPR'20	14.86	0.562	18.06	0.580	-	-
RUAS [24] CVPR'21	18.23	0.720	18.37	0.723	16.55	0.652
URetinex-Net [37] CVPR'22	21.33	0.835	21.16	0.840	24.14	0.928
KinD [44] MM'19	20.86	0.790	14.74	0.641	13.29	0.578
LLFlow [34] AAAI'22	25.19	0.870	26.53	0.892	26.08	0.940
LLFlow-SKF [38] CVPR'23	26.80	0.879	28.19	0.905	28.86	0.953
DRBN [40] CVPR'20	19.39	0.817	20.29	0.831	23.22	0.927
DRBN+ERL [21] CVPR'23	19.84	0.830	-	-	-	-
FECNet [20] ECCV'22	22.03	0.836	20.29	0.831	23.22	0.927
FECNet+ERL [21] CVPR'23	21.08	0.829	-	-	-	-
Retiformer [6] ICCV'23	25.16	0.845	22.80	0.840	25.67	0.930
LACT* [4] ICCV'23	26.49	0.867	26.95	0.888	27.24	0.941
ECMamba (Ours)	**27.69**	**0.885**	**29.24**	**0.908**	**29.94**	**0.959**

Qualitative Results



More details can be found on Github.
Thank you for watching!

https://github.com/LowlevelAI/ECMamba