Decoupling-and-Aggregating for Image Exposure Correction

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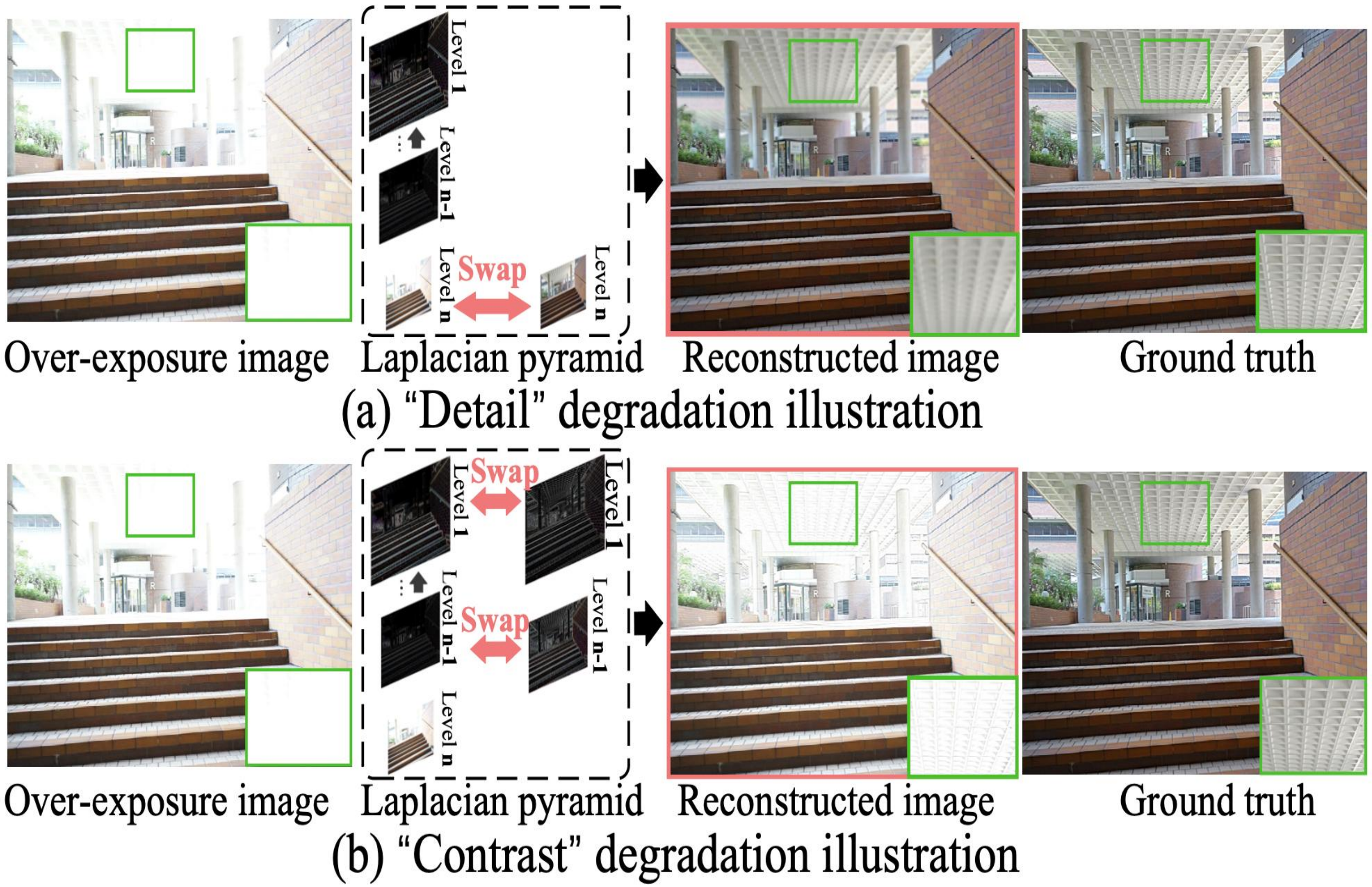
Image Exposure Correction

- Images captured under improper exposure conditions often suffer from under-exposure or over-exposure problems, as shown on the left.

- Image exposure errors can occur due to several factors: errors in measurements of through-the-lens metering, hard lighting conditions, dramatic changes in the brightness level of the scene, and errors made by users in the manual mode.

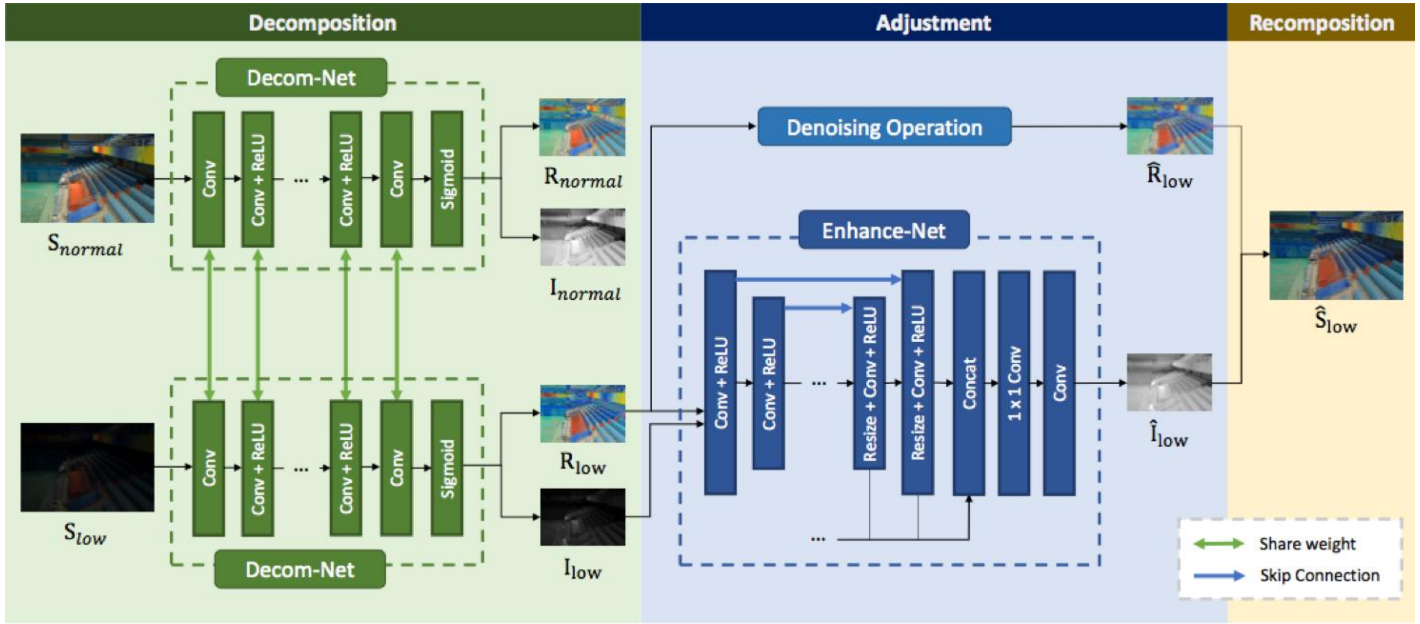
Motivation



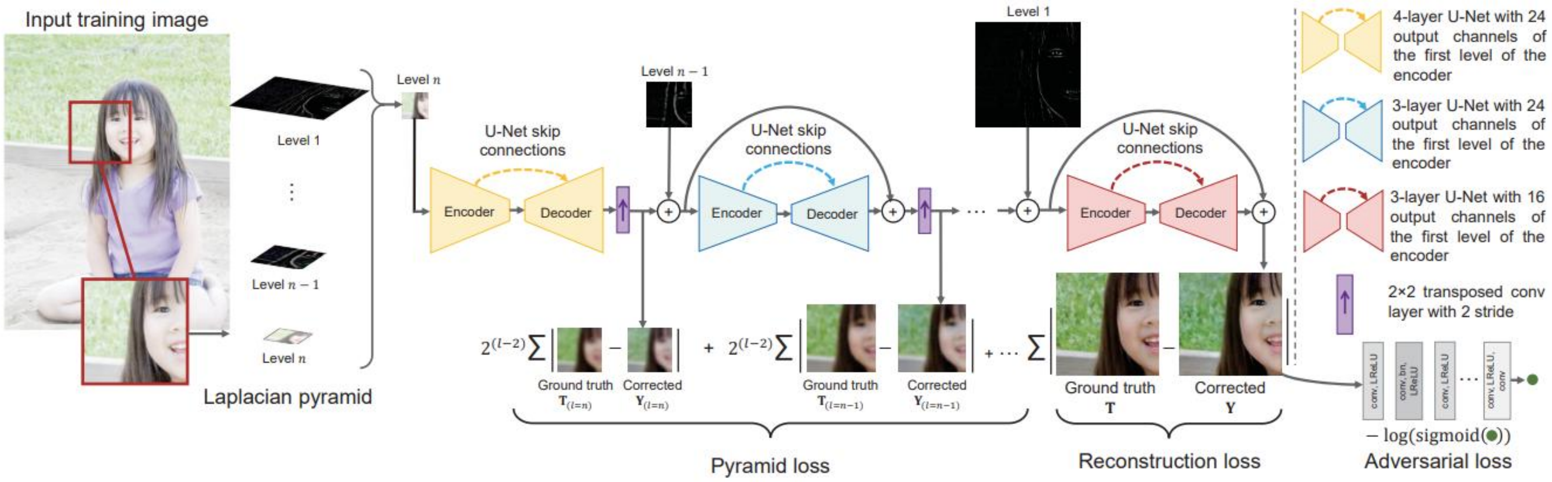
The under and over-exposure images often suffer from contrast degradation and detail distortion.

- **Contrast degradation will destroy the statistical properties of low-frequency components.**
- **Detail distortion will disturb the structural properties of high-frequency components**

Previous Methods

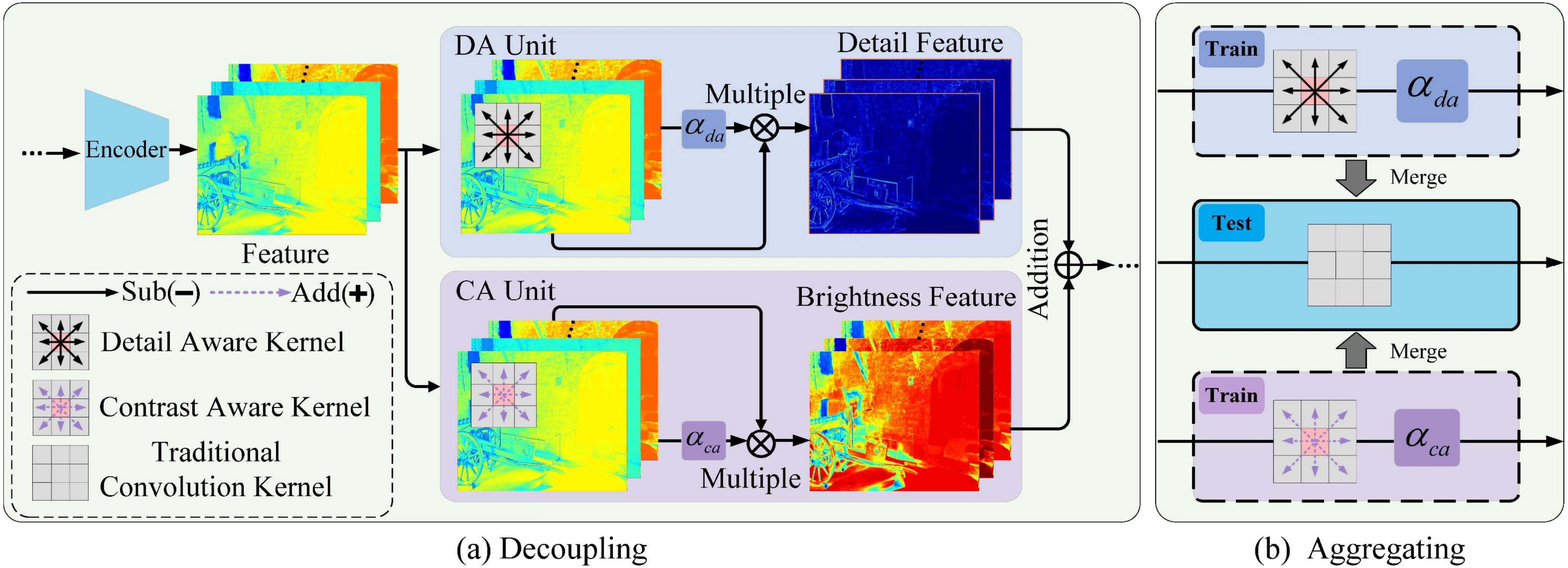


Deep Retinex Decomposition for Low-Light Enhancement



Learning Multi-Scale Photo Exposure Correction

Proposed Method



Overview of our proposed DAConv. (a) In the training phase, each TConv in baselines is substituted by a DAConv. (b) After training, the DA, CA, a_{da} and $a_{ca}$are aggregated into a single TConv again by aggregating.

Experiment Results

ME dataset and SICE dataset.

	ME dataset [2]				SICE dataset [4]			
	Under-exposure		Over-exposure		Under-exposure		Over-exposure	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
RUAS [20]	13.430	0.681	6.390	0.466	7.507	0.246	5.806	0.089
RUAS*	**14.867**+1.437	**0.708**+0.027	**6.940**+0.550	**0.486**+0.020	**8.528**+1.021	**0.356**+0.110	**5.938**+0.132	**0.137**+0.048
Zero-DCE [11]	14.550	0.589	10.400	0.514	15.972	0.653	9.078	0.590
Zero-DCE*	**15.067**+0.517	**0.771**+0.182	**10.847**+0.447	**0.710**+0.196	**16.229**+0.257	**0.656**+0.003	**9.315**+0.237	**0.595**+0.005
RetinexNet [30]	12.130	0.621	10.470	0.595	15.239	0.613	16.863	0.638
RetinexNet*	**12.208**+0.078	**0.607**-0.014	**18.576**+8.106	**0.794**+0.199	**15.637**+0.398	**0.642**+0.029	**17.009**+0.146	**0.645**+0.007
UNet [26]	18.437	0.821	17.440	0.809	16.036	0.650	17.209	0.664
UNet*	**18.524**+0.087	**0.831**+0.010	**17.953**+0.513	**0.822**+0.013	**16.521**+0.485	**0.678**+0.028	**17.239**+0.030	**0.684**+0.020
DRBN [34]	19.740	0.829	19.370	0.832	17.249	0.707	18.275	0.700
DRBN*	**20.630**+0.890	**0.888**+0.059	**19.100**-0.270	**0.878**+0.046	**17.337**+0.088	**0.709**+0.002	**18.896**+0.621	**0.780**+0.080
SID [5]	19.370	0.810	18.830	0.806	17.065	0.692	18.728	0.706
SID*	**19.484**+0.114	**0.829**+0.019	**19.015**+0.185	**0.820**+0.014	**17.539**+0.474	**0.724**+0.032	**18.796**+0.068	**0.714**+0.008
MSEC [2]	20.520	0.813	19.790	0.816	18.291	0.606	17.755	0.626
MSEC*	**21.530**+1.010	**0.859**+0.046	**21.550**+1.760	**0.875**+0.059	**18.949**+0.658	**0.655**+0.049	**17.979**+0.224	**0.660**+0.034
ENC [14]	22.720	0.854	22.110	0.852	18.665	0.696	18.974	0.703
ENC*	**23.320**+0.600	**0.909**+0.055	**22.600**+0.490	**0.909**+0.057	**19.072**+0.407	**0.701**+0.005	**19.176**+0.202	**0.707**+0.004
FECNet [15]	22.960	0.860	23.220	0.875	18.012	0.685	18.496	0.691
FECNet*	**23.150**+0.190	**0.865**+0.005	**23.410**+0.190	**0.880**+0.005	**18.347**+0.335	**0.691**+0.006	**18.893**+0.397	**0.698**+0.007

The bold and **bold*** represent performance training with Vanilla Conv(VC) and proposed DAConv.
The bold and bold represent our cost-free improvement compared to the baselines VC and a slight degradation after using DAConv.

Experiment Results

LOLV1, LOL-V2-R, and LOL-V2-S datasets.

	LOLV1 [30]		LOL-V2-R [34]		LOL-V2-S [34]	
	PSNR↑	SSIM↑	PSNR↑	SSIM↑	PSNR↑	SSIM↑
ZeroDCE [11]	15.296	0.518	12.382	0.448	16.954	0.810
ZeroDCE*	**16.206**+0.910	**0.522**+0.004	**13.445**+1.063	**0.460**+0.012	**17.372**+0.418	**0.820**+0.01
UNet [26]	17.480	0.753	18.449	0.668	18.131	0.843
UNet*	**17.671**+0.191	**0.764**+0.011	**18.533**+0.084	**0.718**+0.050	**20.079**+1.948	**0.878**+0.035
DRBN [34]	19.068	0.790	19.421	0.729	21.012	0.895
DRBN*	**19.190**+0.122	**0.812**+0.022	**19.855**+0.434	**0.747**+0.018	**21.100**+0.088	**0.899**+0.004
SID [5]	18.577	0.789	18.640	0.703	20.801	0.884
SID*	**19.260**+0.683	**0.812**+0.023	**18.892**+0.252	**0.713**+0.01	**22.267**+1.456	**0.910**+0.026
MSEC [2]	18.845	0.679	19.031	0.662	19.582	0.705
MSEC*	**20.895**+2.050	**0.748**+0.069	**20.192**+1.161	**0.670**+0.008	**20.745**+1.163	**0.813**+0.108
ENC [14]	22.310	0.837	21.004	0.802	21.608	0.887
ENC*	**22.856**+0.546	**0.843**+0.006	**21.764**+0.760	**0.839**+0.037	**22.337**+0.729	**0.902**+0.015

The bold and **bold*** represent performance training with Vanilla Conv(VC) and proposed DAConv.
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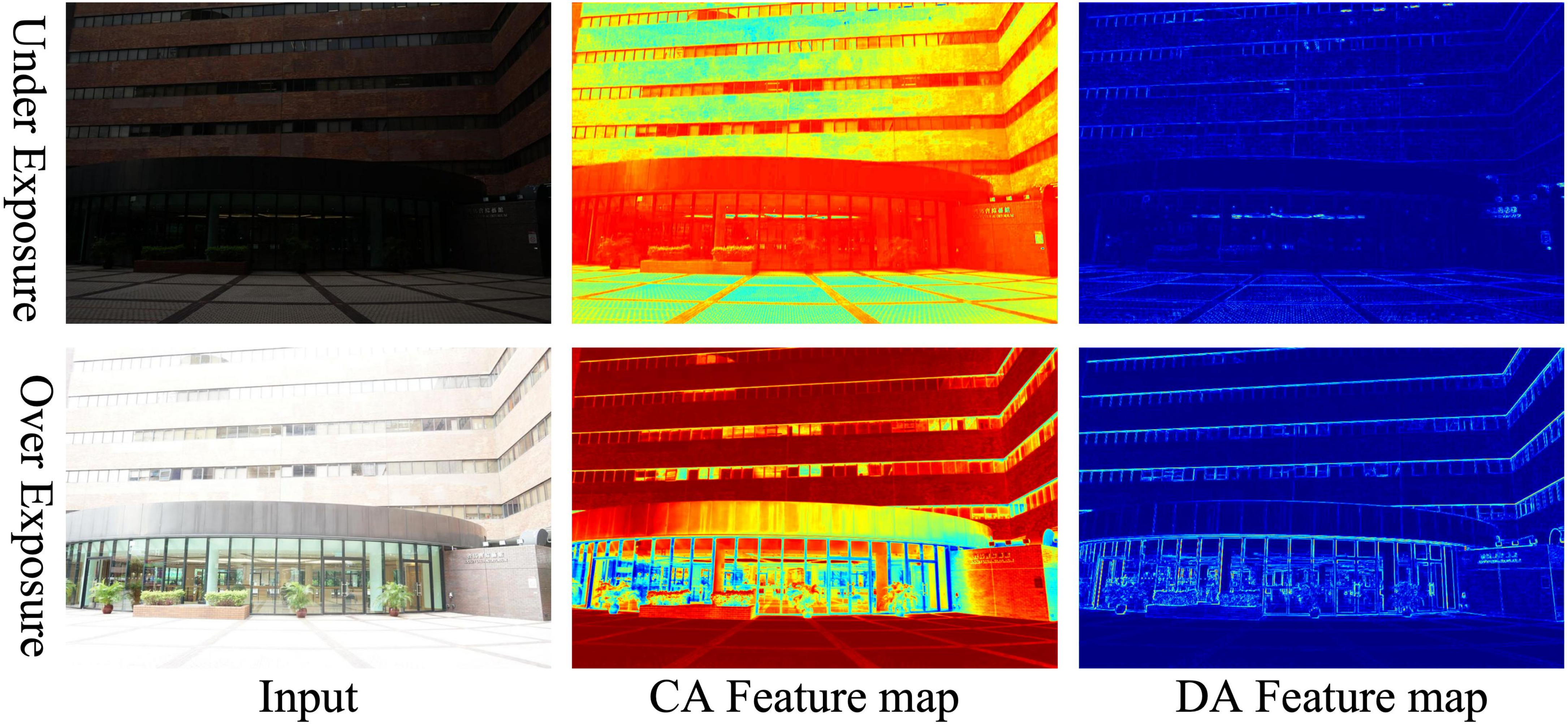
Comparison of Enhanced Results

The Comparison of Enhanced Results on SCIE datasets

Feature visualization



Feature maps of Contrast Aware and Detail Aware Unit

THANK YOU