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Sub-band Adaptive Low Light Image Enhancement Using Wavelet-Based Convolutional Neural Networks

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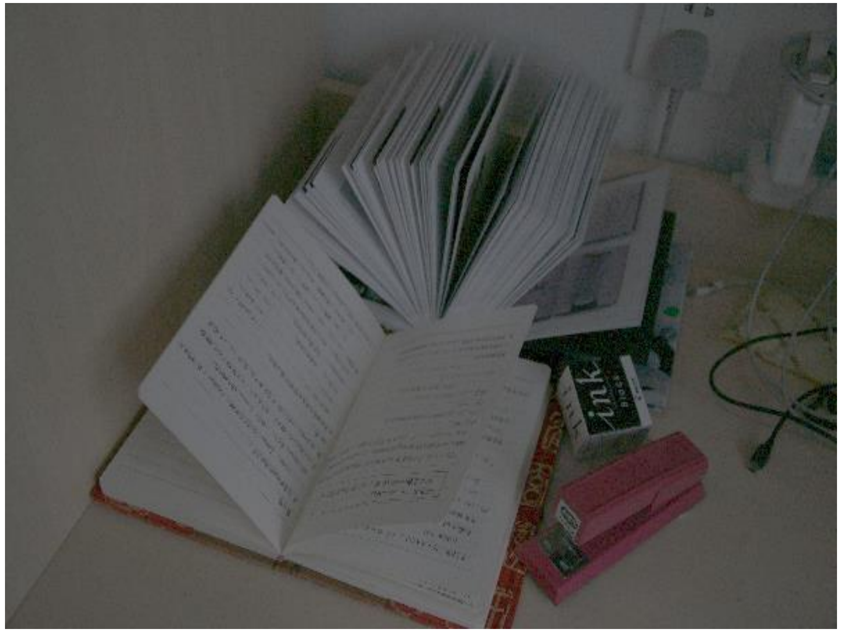
Low light image enhancement

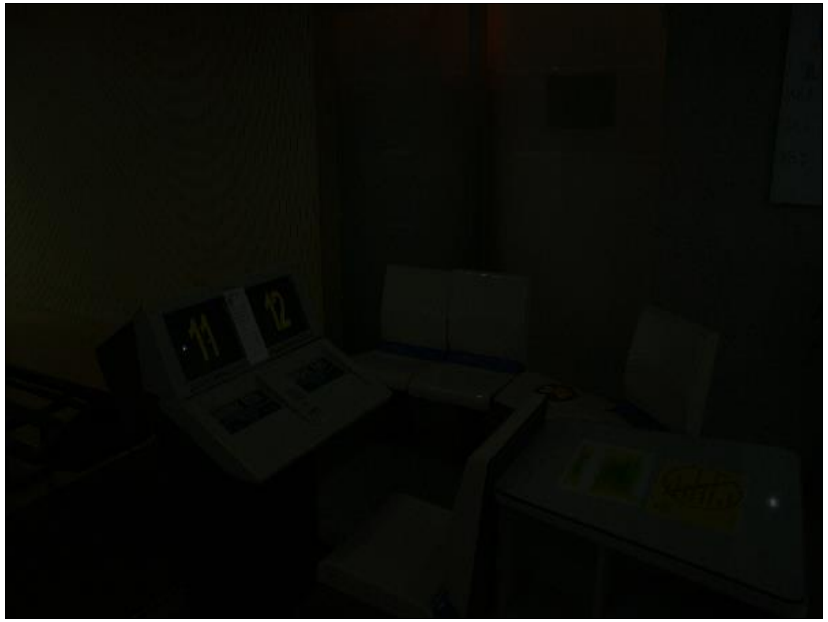
Low light image



Gamma correction

Proposed method

Low light image enhancement



Low light image

Gamma correction

Proposed method

Low light images: Low contrast, much noise and weak color.

Motivation

- **Sub-band adaptive processing**

In wavelet analysis, signal is often decomposed to low- and high-frequency sub-bands, which low-frequency sub-band provides approximate information and high-frequency sub-bands provide image details. Most noise is contained in the high frequency sub-bands.

- **Wavelet transform's advantages**

1) Perfect reconstruction ability to ensure that there is no information loss and redundant information;

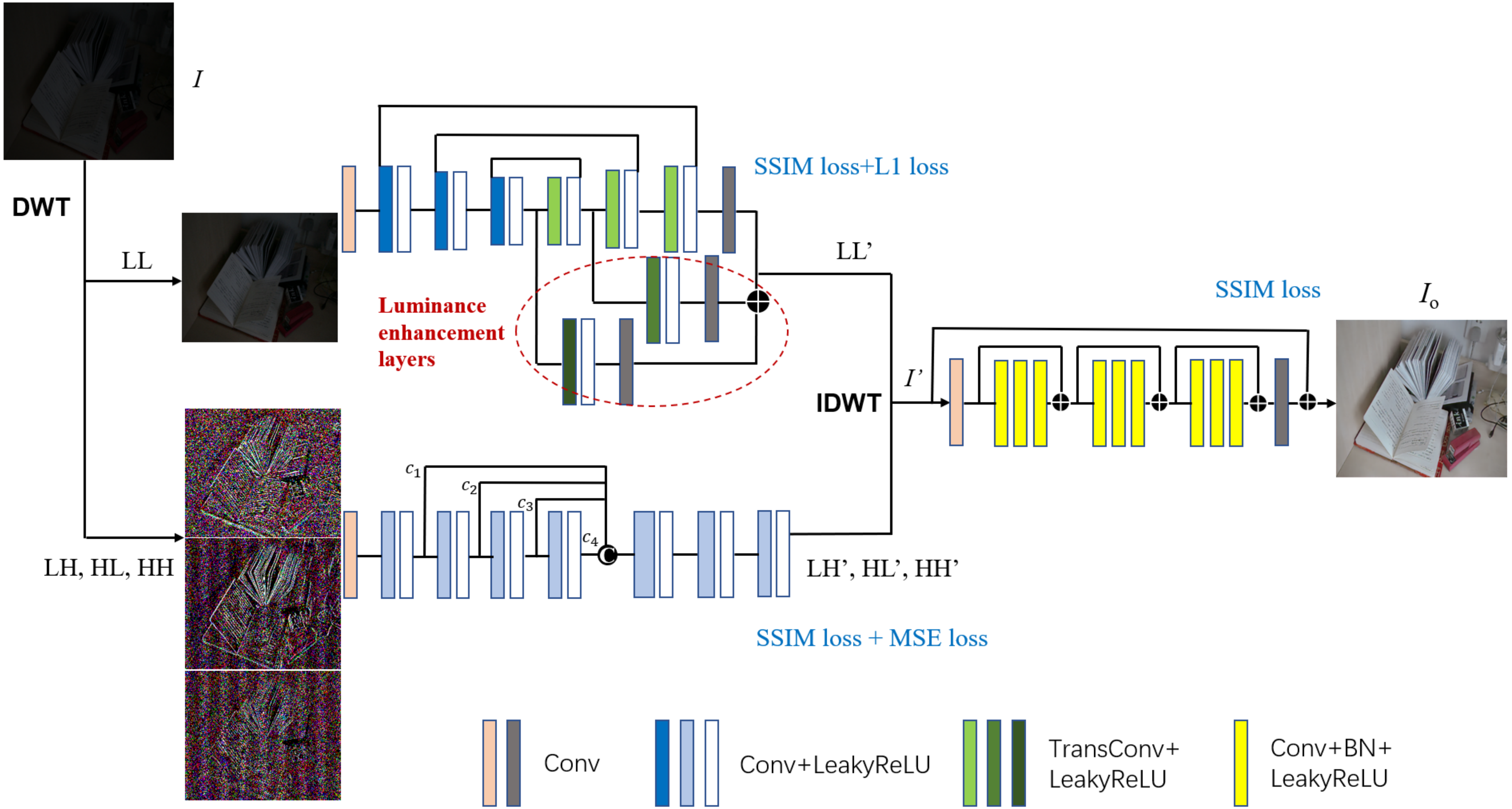
2) Can effectively extract significant information such as textures and edges.

Contributions

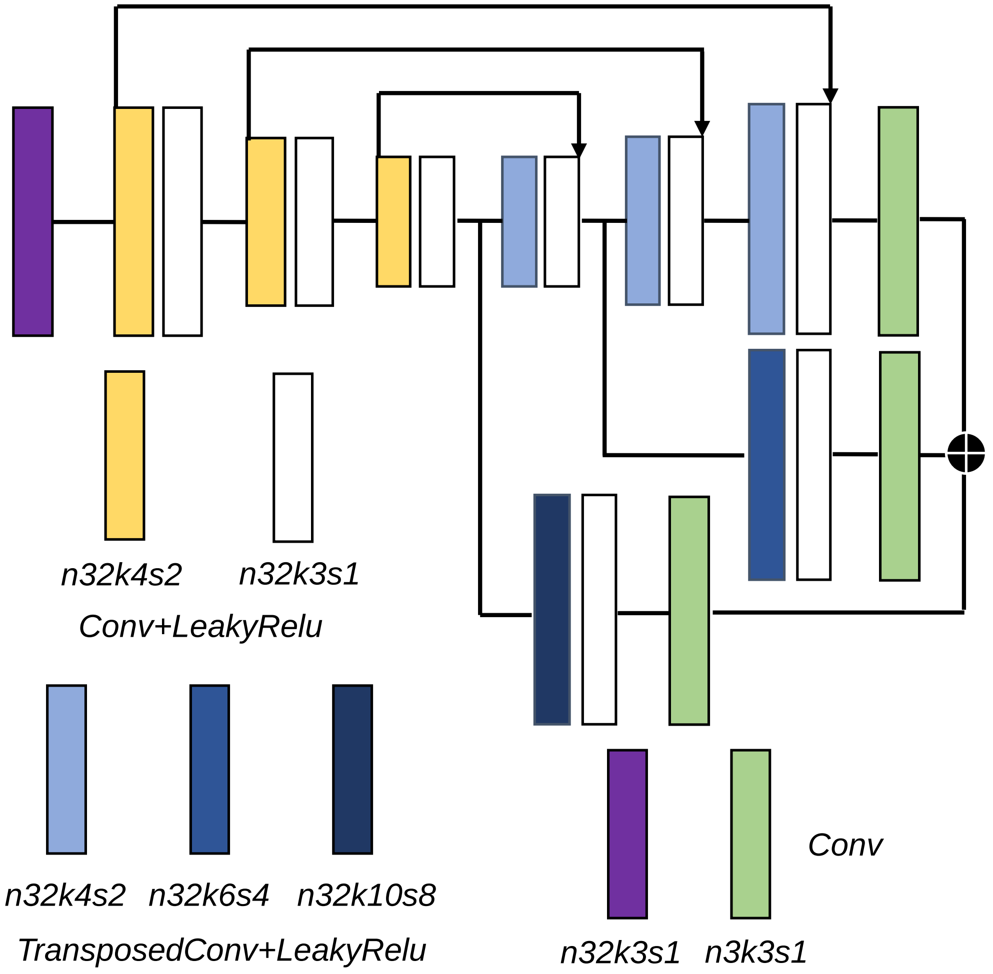
- **Subband adaptive low light image enhancement** based on discrete wavelet transform (DWT)
  - Decompose an image into LL band and HL, LH, HH bands to separately solve different low image problems: low lightness and noise.

- **Well-designed CNN** for low light image enhancement
  - Add the new luminance reinforcement layers into U-net framework to realize global brightness enhancement.
  - Design a new Feature Fusion network to achieve denoising and enhancement on the LH, HL, HH bands.
  - Introduce a chain of residual blocks as Refinement network to complete image details.

Proposed Method



Proposed Method: Contrast enhancement for LL band



Adopt **U-Net** as the basic enhancement framework to increase local receptive fields for connecting more pixels.

Only using U-Net leads to the image background to be darker, we introduce **luminance reinforcement layers** for extending contrast dynamic range.

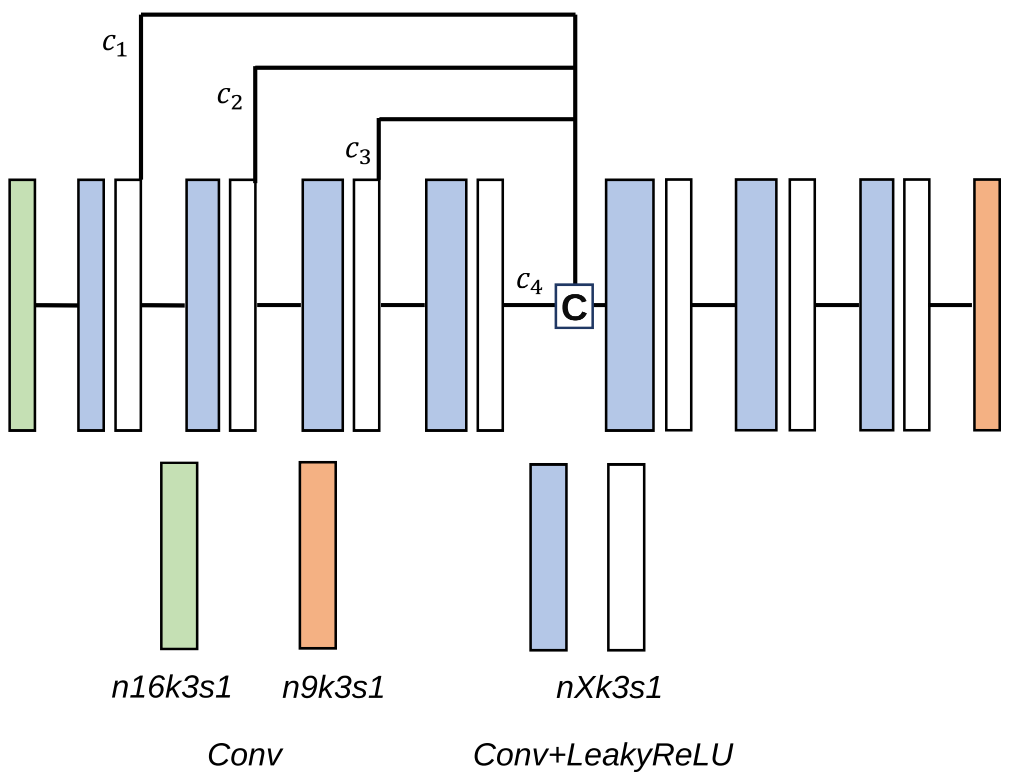
Proposed Method: Loss function for LL band

$$\boldsymbol{L_{CE} = w_1 L_{re} + w_2 L_{col}}$$

- Use the SSIM loss to define $L_{re} = \frac{1}{N}\sum_p 1 - SSIM(F(I(p)), gt)$($gt$ means LL band of ground truth), which can take brightness, contrast and structure into consideration.

- Only use SSIM loss results in brightness change and color deviation, so introduce L1 Loss to define $L_{col} = \|F(I) - gt\|_1$ for keeping brightness and color constancy.

Proposed Method: Noise reduction for HL, LH, HH bands



Based on that shallow network extracts the detail information and deep network extracts the high level semantic information and most of noise exists in the detail information,

Thus, we set low parameters(<0.5) on the shallow layers and high parameters(>1) on the deep layers for noise reduction, then fuse adjusted features for reconstruction.

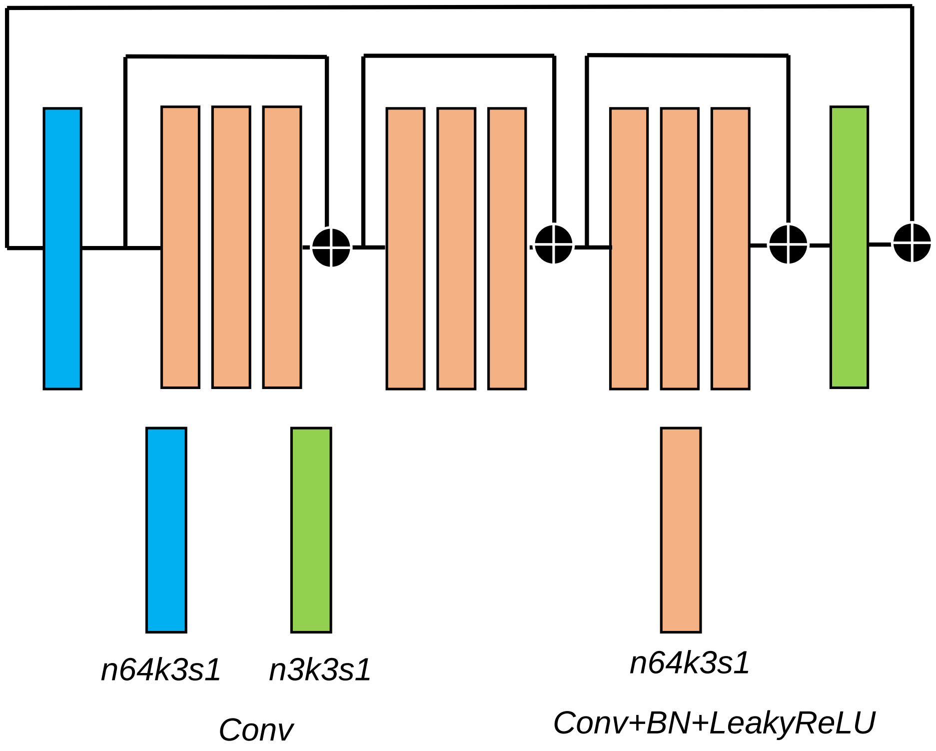
Proposed Method: Loss function for HL, LH, HH bands

$$\boldsymbol{L_{NR} = L_{re} + \beta L_{intensity}}$$

- Also use the SSIM loss to define $L_{re} = \frac{1}{N}\sum_p 1 - SSIM(F(I(p)), gt)$($gt$ means high bands of ground truth).

- SSIM loss results in weaker constrains on the difference of the intensity distribution, so introduce L2 Loss to define $L_{intensity} = \|F(I) - gt\|_2$ for keeping intensity distribution.

Proposed Method: Refinement for Inverse transform result



As a result of the IDWT results occur edge blur and color shifts, so using **a series of residual blocks** as the fine-tune network to extract useful information for recovering lost textural details in the component network.

$$\boldsymbol{L_{refin}} = \frac{\mathbf{1}}{\boldsymbol{N}} \sum_{\boldsymbol{p}} \mathbf{1} - \boldsymbol{SSIM}(\boldsymbol{F}(\boldsymbol{I}(\boldsymbol{p})), \boldsymbol{gt})$$

Use SSIM loss to reduce the difference between the final result and ground truth in brightness, contrast and structure.

Experimental Details

HW: GTX 2080 TI

SW: Python + PyTorch

Training details:

1) Contrast enhancement network: batch_size=64 epoch=500 lr=1e-4 optimizer=Adam

2) Noise redution network: batch_size=64 epoch=500 lr=1e-4 optimizer=Adam C=[0.2, 0.3, 2, 3]

3) Refinement network: batch_size=16, epoch=50, lr=1e-4 optimizer=Adam

Evaluation metrics: PSNR, SSIM, No-Reference IQA(NIQE)

Compared methods:

- RetinexNet: Deep Retinex Decomposition for Low-Light Enhancement, Retinex Net.
- Zero-DCE: Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement.
- Self-supervised: Self-supervised Image Enhancement Network: Training with Low Light Images Only.
- LIME: Low-light Image Enhancement via Illumination Map Estimation.
- DLN: Lighting Network for Low-Light Image Enhancement.

Experimental results

Input

GT

LIME

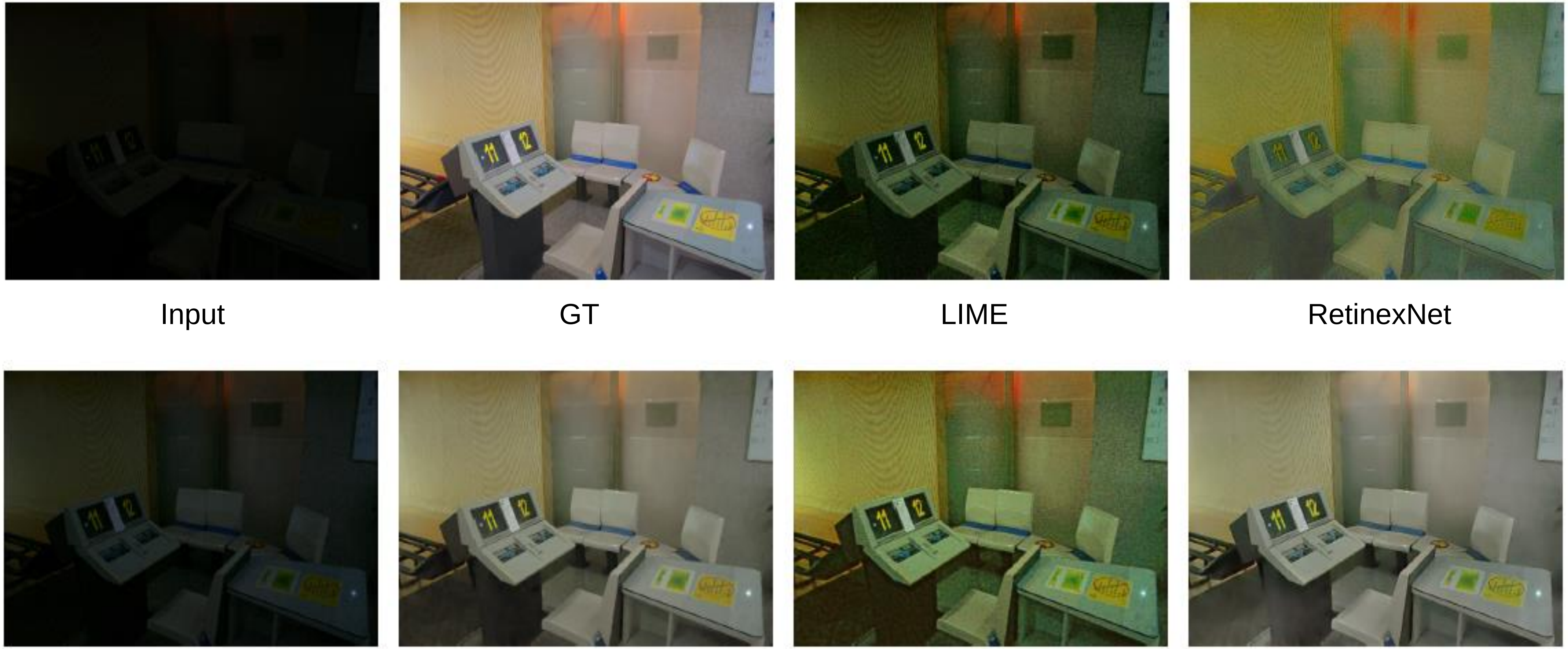
RetinexNet

Zero-DCE

DLN

Self-Supervised

Proposed



Visual comparison on LOL dataset

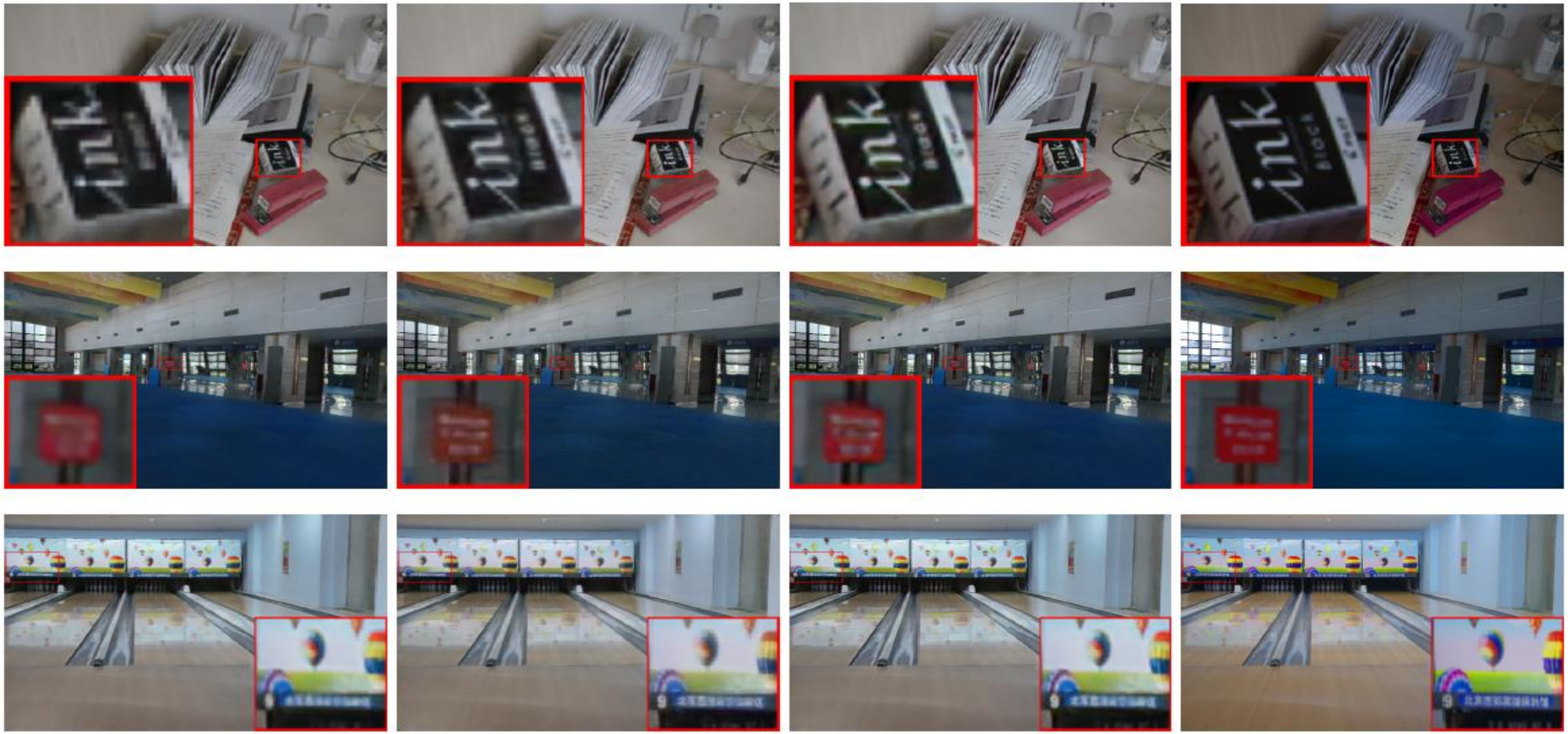

Input
GT
LIME
RetinexNet
Zero-DCE
DLN
Self-Supervised
Proposed

Visual comparison on NPE dataset

The images on the right turn represents the results on LIME, RetinexNet, Zero-DCE, DLN, Self-Supervised, Proposed Method.

Visual comparison on ExDark dataset

Ablation study



Without noise reduction | Without refinement | Final results | Ground Truths

Quantitative measurements

Dataset	LOL			NPE			ExDark
Methods	PSNR	SSIM	NIQE	PSNR	SSIM	NIQE	NIQE
LIME	12.65	0.5469	9.127	12.11	0.6142	13.61	**11.40**
RetinexNet	18.40	0.7320	9.730	17.14	0.7014	**12.95**	12.16
Zero-DCE	13.14	0.5728	11.304	10.32	0.4554	15.26	17.51
DLN	23.82	0.8543	4.915	14.79	0.6777	13.34	15.04
Self-supervised	22.06	0.7201	4.793	17.12	0.7280	15.36	18.84
Proposed	**24.93**	**0.8759**	**4.332**	**18.32**	**0.7473**	15.45	16.61

Conclusions

- DWT is a useful method on low light image enhancement by adaptively processing low frequency component (LL band) and high frequency components (HL, LH, HH bands).

- Experimental results show that the proposed method can effectively eliminate noise while achieving image enhancement and its performance is better than the state-of-the-art methods.

Thank You!