LLDE: ENHANCING LOW-LIGHT IMAGES WITH DIFFUSION MODEL

30th ICIP 2023 Kuala Lumpur

Paper ID 1917

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Introduction

- We bring a new perspective to address the unsolved issue of limited generalization capability in low-light image enhancement.
- We believe that dividing the enhancement process into many small steps and performing them gradually will allow the model to learn a more robust representation of the data.
- To put this concept into practice, we proposed to adopt a diffusion model for low-light image enhancement.
- The code is publicly available at the GitHub link in the QR code.

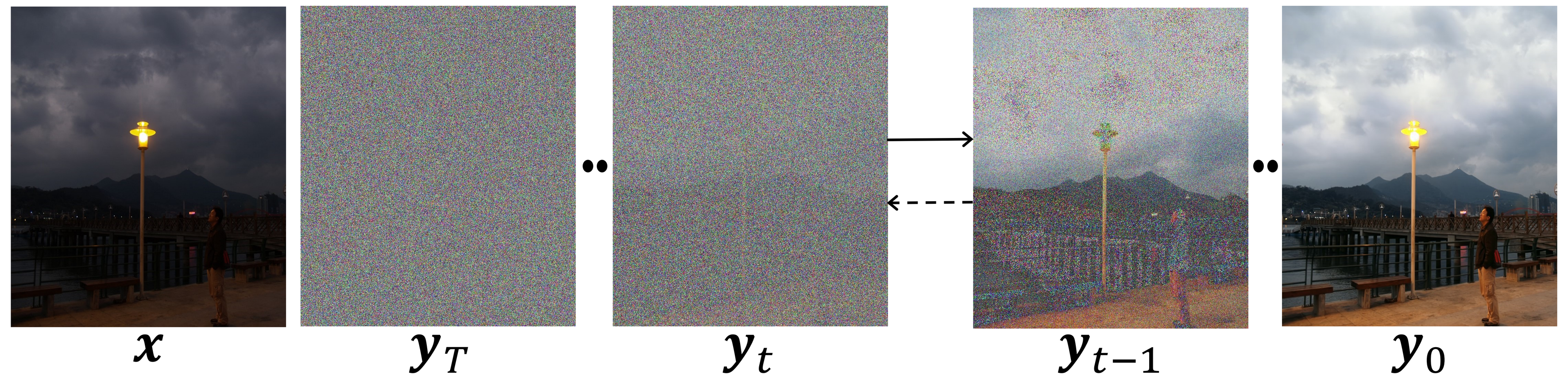
Methodology

Denoising Diffusion Probabilistic Models

- Diffusion Probabilistic Model is a generative model, which work by gradually corrupt the input image using Gaussian noise, until it is in-distinguish from Gaussian noise.
- Then, it is trained to recover the data by reversing this noising process.

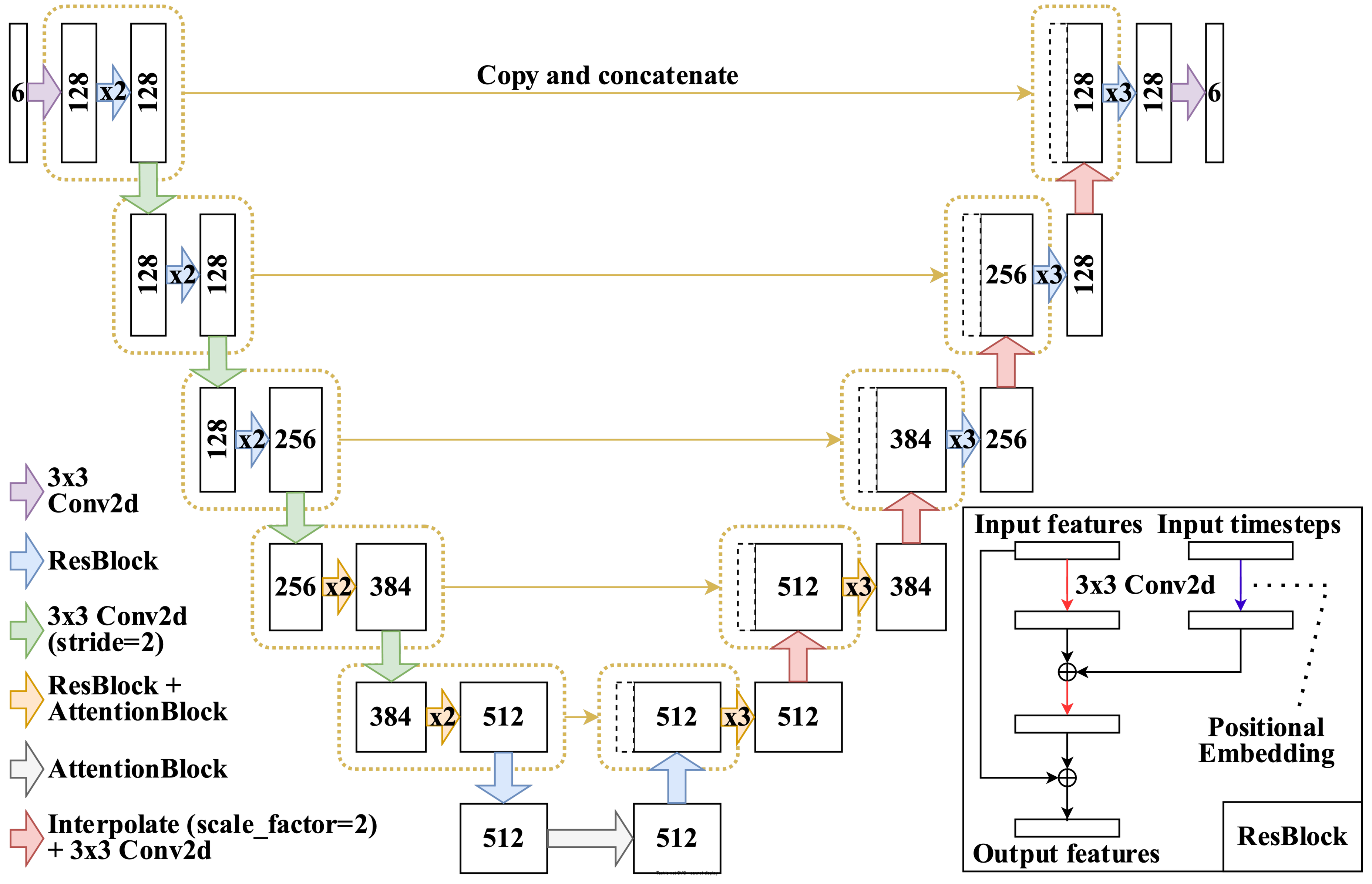
Conditional Diffusion Probabilistic Models

- Forward diffusion (dashed arrow) is done on the target normal-light image $\boldsymbol{y}_0$, and the model learns to sample from the posterior distribution while conditioned on the input low-light image $\boldsymbol{x}$.
- As such, the enhancement process is divided into many small steps in this process. Guided by the learned latent space of normal-light image distribution, conditional reverse diffusion (solid arrow) gradually estimates the noise to neutralize the noise injected and enhance the input low-light image $\boldsymbol{x}$.



Proposed LLDE: Low-Light Diffusive Enhancement

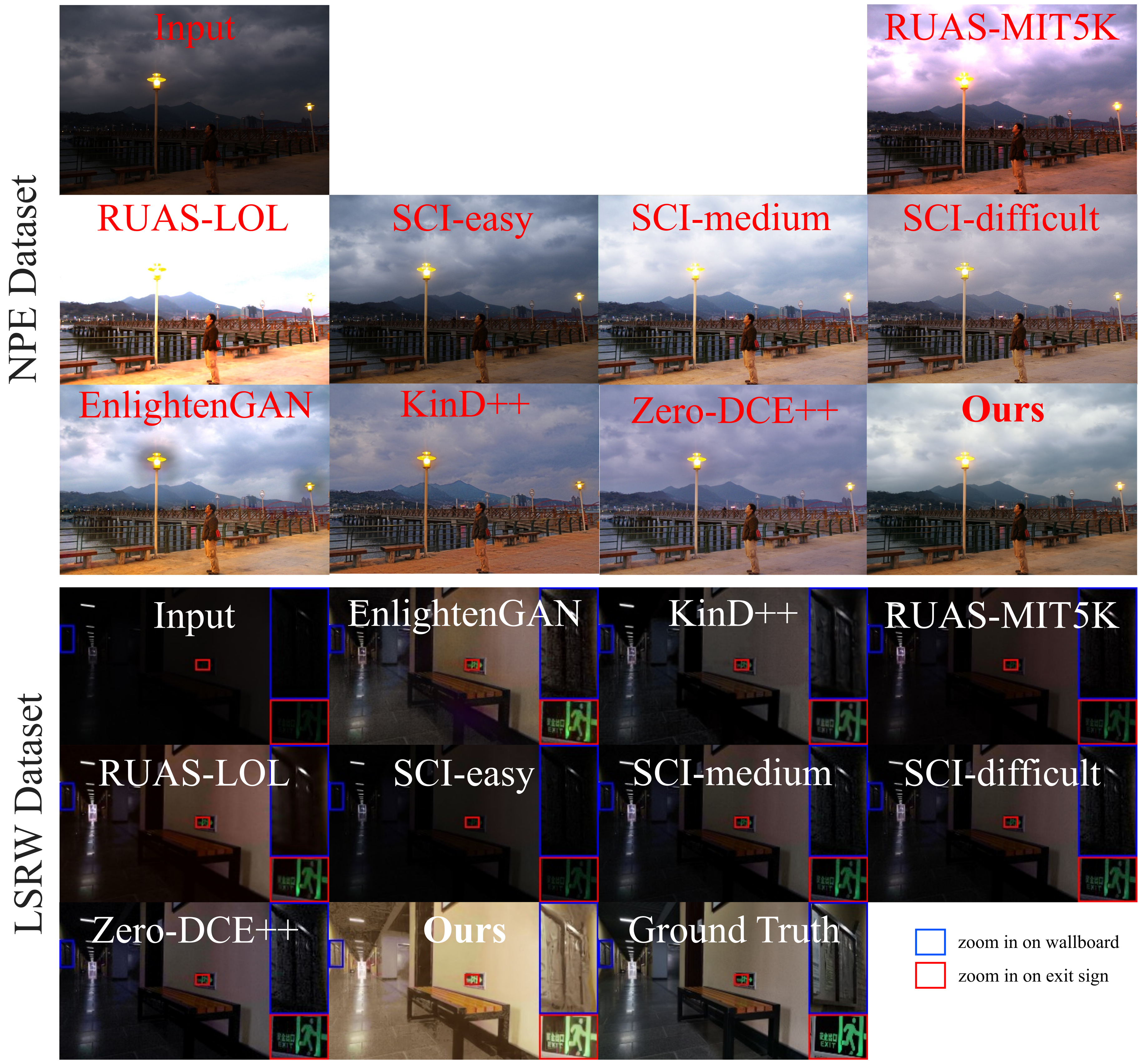
- LLDE conditions the input low-light image $\boldsymbol{x}$ in the reverse diffusion process by concatenating it with noisy enhanced output $\boldsymbol{y}_t$.
- LLDE uses a UNet-like network, as illustrated below.
- To produce more visually appealing enhanced images, we incorporated two techniques into LLDE:
  - improve the noise schedule from linear to cosine.
  - predict mean and variance of noise in the reverse diffusion process.
- To reduce the enhancement time, we adopt the sampling strategy decrease the diffusion time steps T from 1000 to 25.



Discussion / Conclusion

- This paper proposes a novel approach to low-light image enhancement using the diffusion model.
- Empirical results show that LLDE outperforms recent state-of-the-art models in terms of quantitative and qualitative performance, showing multi-steps enhancement is more effective.

Results and Comparison



Methods (on LSRW)	PSNR↑	SSIM↑	LPIPS↓	NIQE↓
EnlightenGAN	**17.1039**	0.5037	0.3270	<u>3.4847</u>
KinD++	16.1745	0.4422	0.3468	**3.4126**
RUAS-MIT5K	13.0702	0.3791	0.3777	4.2689
RUAS-LOL	14.2904	<u>0.5237</u>	0.4659	5.4262
SCI-easy	11.8472	0.3313	0.3976	4.3690
SCI-medium	15.2718	0.4484	0.3219	3.8473
SCI-difficult	15.2093	0.4313	0.3254	3.9185
Zero-DCE++	16.2833	0.4844	<u>0.3175</u>	3.7678
LLDE (Ours)	<u>16.7430</u>	**0.5301**	**0.3045**	3.9306