Learning-based methods in low-light image enhancement

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Introduction

- weak light illumination
- low fluorescence quantum efficiency
- highly scattering media
- short exposure time
- …

Challenges

- Low photon counts
- Low signal-to-noise ratio
- Shot noise & task-specific noise
- Color distortion
- Lack of extremely low light datasets

Traditional Methods

- total variation, sparse coding, NLM, BM3D…
- histogram equalization (HE)
- retinex, multi-scale retinex (MSR)

limitation:

- limited adaptivity and performance
- fail in extremely low light conditions (average photon< 1/pixel)

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low light image datasets

datasets	introduction
SID: See in the Dark (2018)	RAW format; low-light image: ~ 5000 pics normal-light image: ~ 500 pics
LOL: LOw-Light dataset (2018)	PNG format (with ISP) 500 low/normal-light image pairs
ExDARK: Exclusively Dark Dataset (2019)	collected from the Internet low-light image: ~ 7500 pics
ReNOIR: Real Low-Light Image Noise Reduction (2017)	RAW format; 120 scene, high-resolution image pairs
VIP-LowLight: Eight Natural Images Captured in Very Low-Light Conditions (2016)	A few images captured in low light conditions

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low light image datasets

current problem:

- the lack of extremely low light datasets (<1photon / pixel)
- the lack of microscopic low light datasets
- the lack of wildly accepted benchmark datasets

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Overview

2015	LLNet A Deep Autoencoder Approach to Natural Low Light Image Enhancement
2017	DSLR Quality Photos on Mobile Devices with Deep ConvolutionalNetworks
2017	MSRNet Low Light Image Enhancement using Deep Convolutional Network
2017	LLCNN A Convolutional Neural Network for Low light Image Enhancement
2017	LIME Low light Image Enhancement via Illumination Map Estimation
2017	Deep Bilateral Learning for Real Time Image Enhancement
2018	DeepISP Towards Learning an End to End Image Processing Pipeline
2018	Getting to Know Low Light Images with The Exclusively Dark Dataset

2018	Deep Retinex Decomposition for Low Light Enhancement
2018	Learning to see in the dark
2019	End to End Denoising of Dark Burst Images using Recurrent Fully Convolutional Networks
2019	GLADNet: Low Light Enhancement Network with Global Awareness
2019	Kindling the Darkness: A Practical Low Light Image Enhancer
2019	Learning Digital Camera Pipeline for Extreme Low Light Imaging
2019	A Pipeline Neural Network for Low Light Image Enhancement
2019	Underexposed Photo Enhancement using Deep Illumination Estimation

Learning-Based Method

A Bit Too Much? High Speed Imaging from Sparse Photon Counts

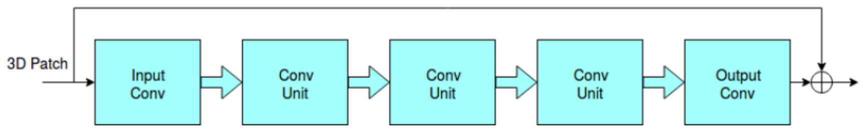

Fig. 3. One residual unit from the proposed ConvNet architecture. Overall, the network consists of K such cascaded residual blocks.

synthetic datasets

Measure	3DCNN1B	3DCNN1B (5)	3DCNN2B	3DCNN2B (5)
PSNR	25.44	25.37	27.40	26.86
SSIM	0.744	0.740	0.815	0.803

real datasets

Measure	[41]	VBM4D [11]	[12]	3DCNNR
PSNR	28.53	30.51	31.41	35.54
SSIM	0.7328	0.7816	0.8218	0.909

- **application:**
  - high speed imaging enhancement with SPAD (1 bit mode, 156k fps)
- **basic model :**
  - 3D-ResNet
- **dataset :**
  - synthetic / real dataset
- **light level :**
  - photon level

[1] P. Chandramouli, etc., "A Bit Too Much? High Speed Imaging from Sparse Photon Counts," in *ICCP 2019*

Learning-Based Method

A Bit Too Much? High Speed Imaging from Sparse Photon Counts

Synthetic dataset training network testing:

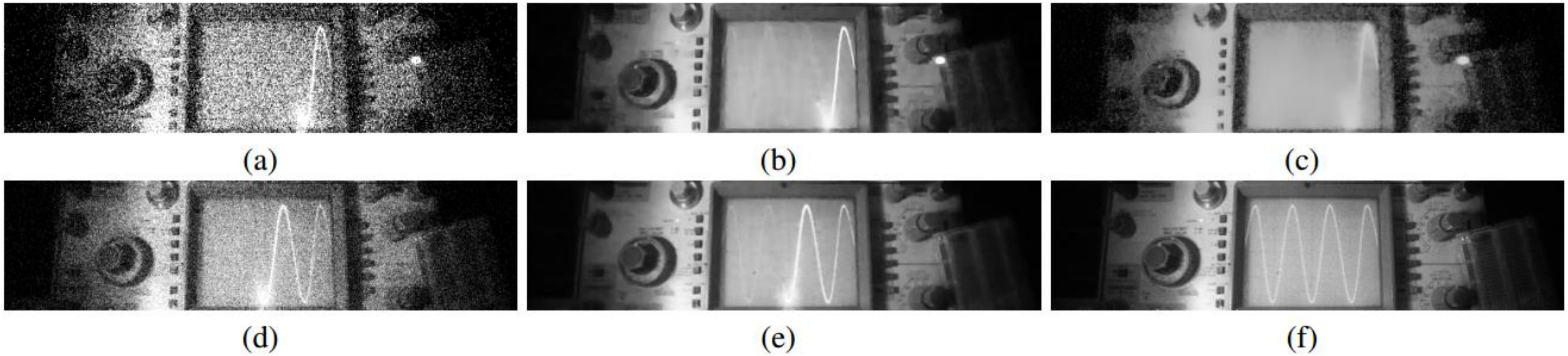

Fig. 5. (a) A 2-bit frame from the input to our algorithm captured at 78000 fps, and (b) corresponding resultant frame (3DCNN2B). (c) Output of [12]. (d) A 4-bit frame, and (e) corresponding output from 3DCNNR. (f) Average of 120 4-bit frames.

[1] P. Chandramouli, etc., "A Bit Too Much? High Speed Imaging from Sparse Photon Counts," in *ICCP 2019*

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A Bit Too Much? High Speed Imaging from Sparse Photon Counts

Real dataset training network testing:

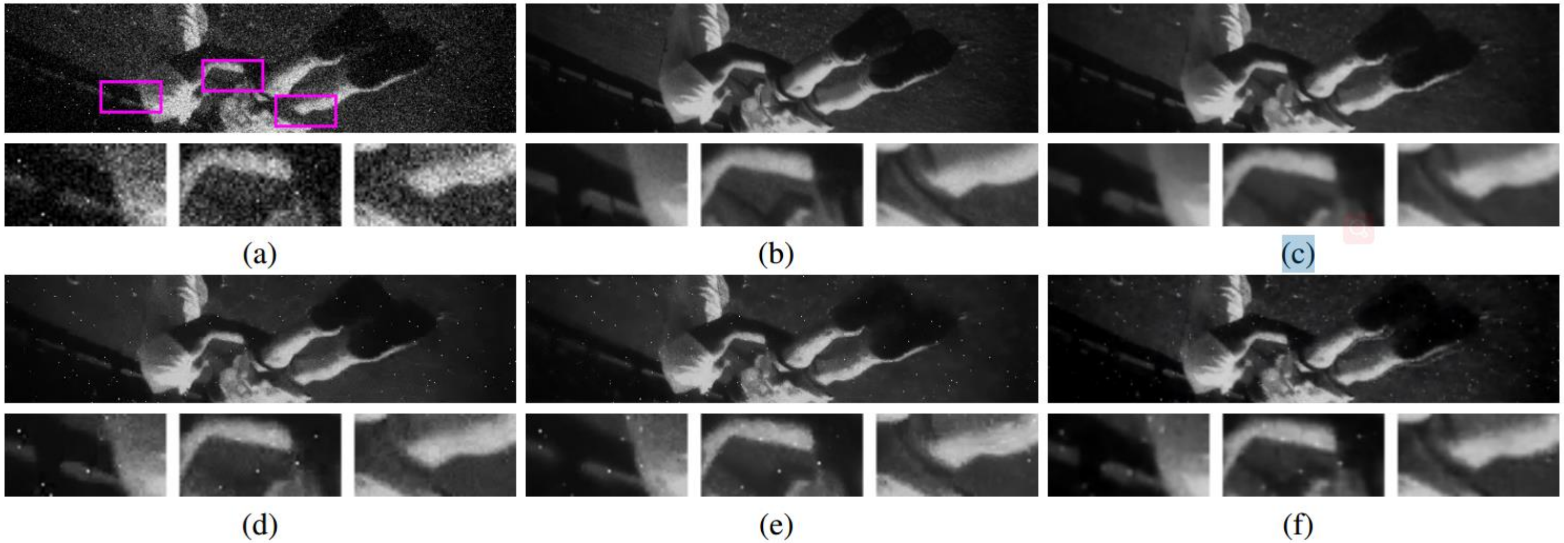
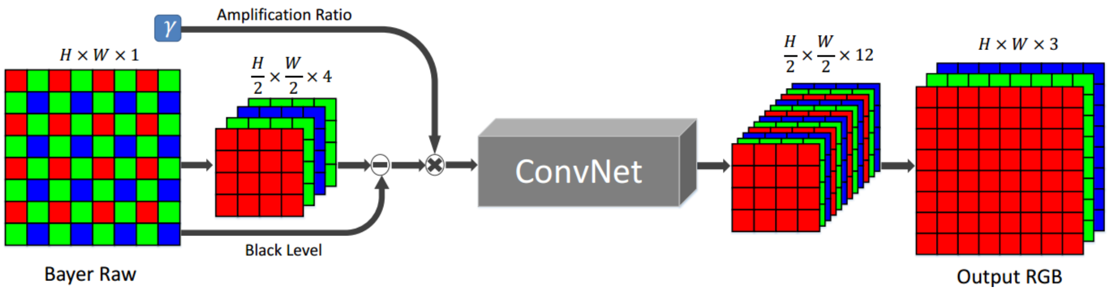


Fig. 11. A representative example from our real test set. (a) A 4-bit frame from the input sequence. (b) Corresponding high-bit resolution image. Frame from recovered video using (c) 3DCNNR, (d) [11], (e) [12] and (f) [41].

[1] P. Chandramouli, etc., "A Bit Too Much? High Speed Imaging from Sparse Photon Counts," in *ICCP 2019*

Learning-Based Method

Learning to See in the Dark



	Sony x300 set	Sony x100 set
Ours > BM3D	92.4%	59.3%
Ours > Burst	85.2%	47.3%

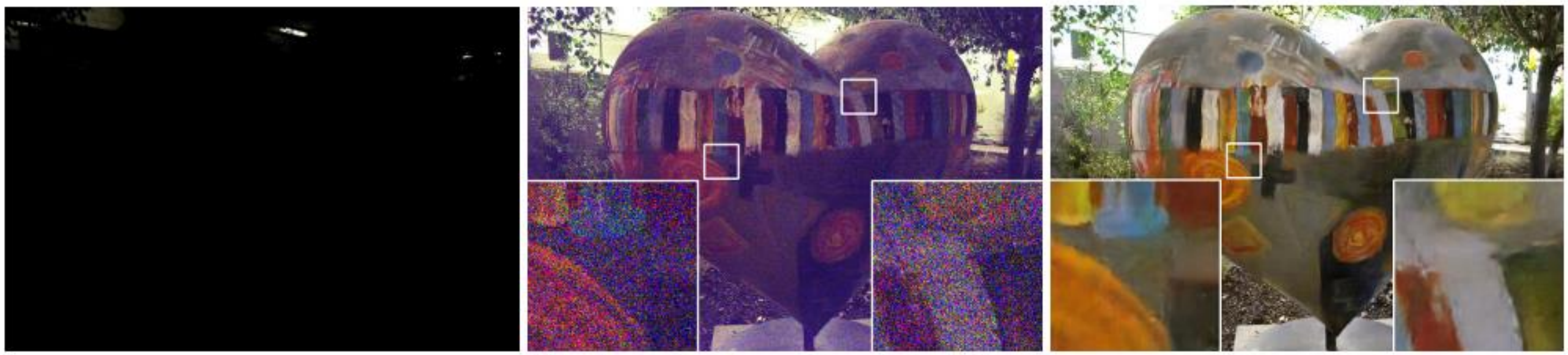
Table 2. Perceptual experiments were used to compare the presented pipeline with BM3D and burst denoising. The experiment is skewed in favor of the baselines, as described in the text. The presented single-image pipeline still significantly outperforms the baselines on the challenging x300 set and is on par on the easier x100 set.

- **basic model:**
  - U-Net (encoder-decoder)
- **dataset:**
  - real dataset: SID (~ 5k)
- **light level:**
  - 0.03lux - 5 lux
- **limitation:**
  - No HDR tone mapping
  - SID contains no humans and dynamic objects
  - not fast enough for real-time

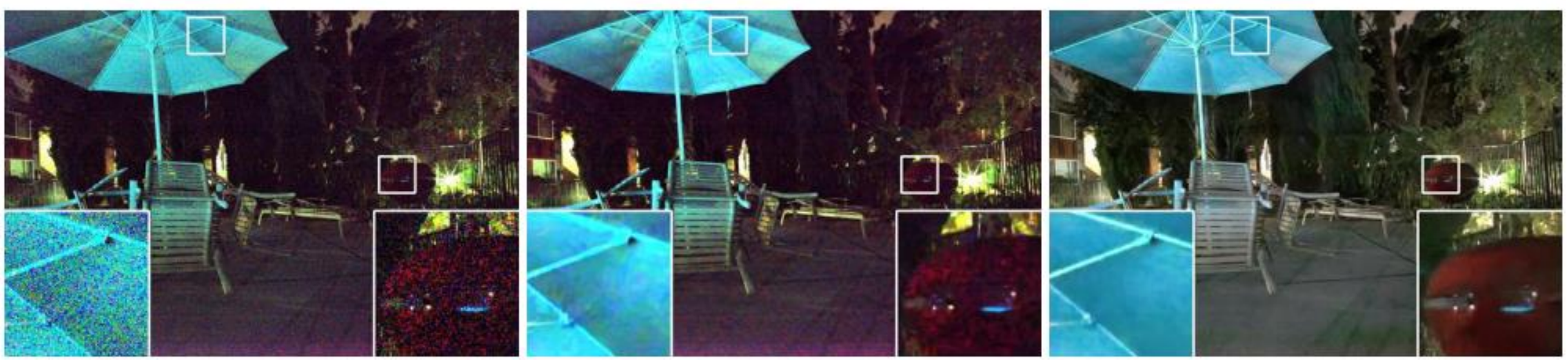
[1] C. Chen, Q. Chen, J. Xu, and V. Koltun, “Learning to See in the Dark,” CVPR 2018

Learning-Based Method

Learning to See in the Dark



(a) JPEG image produced by camera (b) Raw data via traditional pipeline (c) Our result

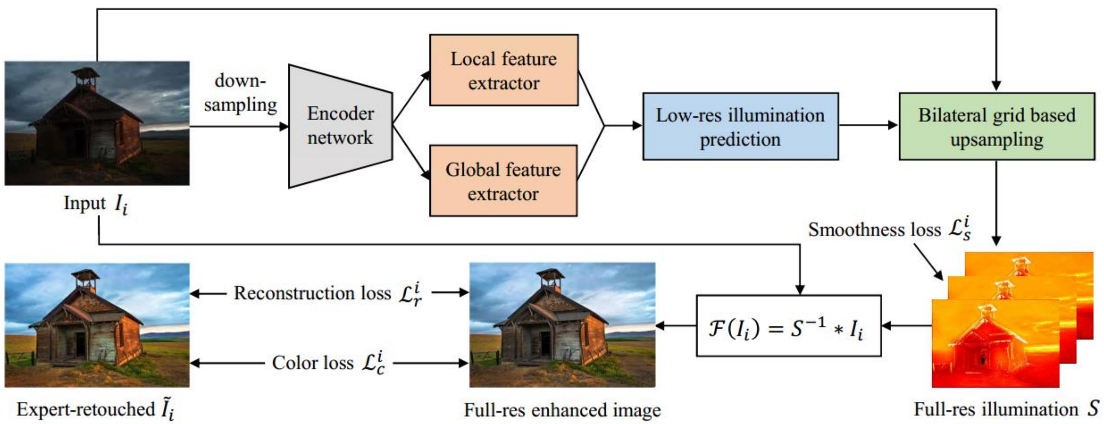


(a) Traditional pipeline (b) ... followed by BM3D denoising (c) Our result

[1] C. Chen, Q. Chen, J. Xu, and V. Koltun, “Learning to See in the Dark,” CVPR 2018

Learning-Based Method

Underexposed Photo Enhancement using Deep Illumination Estimation



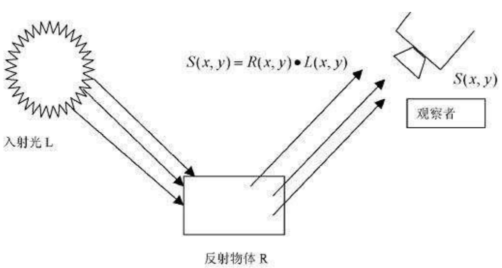


Table 1: Quantitative comparison between our method and state-of-the-art methods on our dataset (w/o - without).

Method	PSNR	SSIM
HDRNet [13]	26.33	0.743
DPE [9]	23.58	0.737
White-Box [15]	21.69	0.718
Distort-and-Recover [22]	24.54	0.712
Ours w/o $\mathcal{L}_r$, w/o $\mathcal{L}_s$, w/o $\mathcal{L}_c$	27.02	0.762
Ours with $\mathcal{L}_r$, w/o $\mathcal{L}_s$, w/o $\mathcal{L}_c$	28.97	0.783
Ours with $\mathcal{L}_r$, with $\mathcal{L}_s$, w/o $\mathcal{L}_c$	30.03	0.822
Ours	**30.97**	**0.856**

basic model:

- Retinex + DNN

dataset:

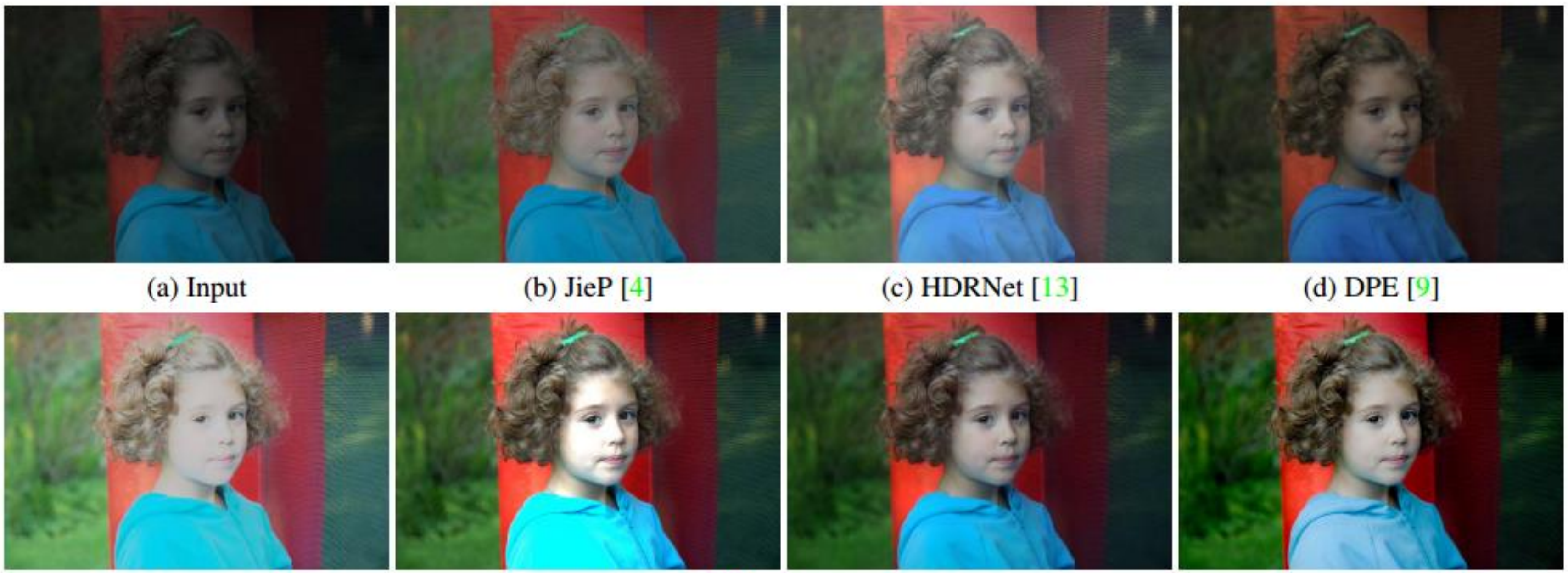
- real dataset: online pics + lightroom; unreleased (~ 3k)

- **forecast:**
  - + denoising module
  - image → video
  - address the nearly black regions

[1] R. Wang, etc., "Underexposed Photo Enhancement Using Deep Illumination Estimation," in CVPR 2019

Learning-Based Method

Underexposed Photo Enhancement using Deep Illumination Estimation



(a) Input (b) JieP [4] (c) HDRNet [13] (d) DPE [9]

(e) White-box [15] (f) Distort-and-Recover [22] (g) Our result (h) Expert-retouched

[1] R. Wang, etc., “Underexposed Photo Enhancement Using Deep Illumination Estimation,” in CVPR 2019

Learning-Based Method

Conclusion

- **Applications:**

  visual enhancement, high speed imaging

- **Physical models：**

  Retinex, Camera Response Model (CRM), noise model

- **Network structures:**

  Autoencoder, ResNet, U-Net, GAN, hybrid net

- **Datasets:**

  synthetic/real datasets; few benchmarks; non-unified standards

- **Challenges:**

  extremely low light image, color distortion, noise, generalization…

Prospects

Future work

- **Datasets:**
  - extreme low light dataset
  - microscopic low light datasets
  - benchmark datasets with unified standards
- **Algorithms:**
  - generalization ability
  - real time performance
  - physical model support

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Thanks for your attention

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