深蓝学院
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更高质量的成像

课程2-图像噪声深入分析与处理

关于噪声去除的补充知识

Understanding the in-camera rendering pipeline & the role of AI and deep learning

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https://www.eecs.yorku.ca/~mbrown/ICCV2023_Brown.html

A High-Quality Denoising Dataset for Smartphone Cameras

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关键资料来源及致谢

Learning to See in the Dark

Chen Chen
UIUC

Qifeng Chen
Intel Labs

Jia Xu
Intel Labs

Vladlen Koltun
Intel Labs

(a) Camera output with ISO 8,000 (b) Camera output with ISO 409,600 (c) Our result from the raw data of (a)

关键资料来源及致谢

Practical Deep Raw Image Denoising on Mobile Devices

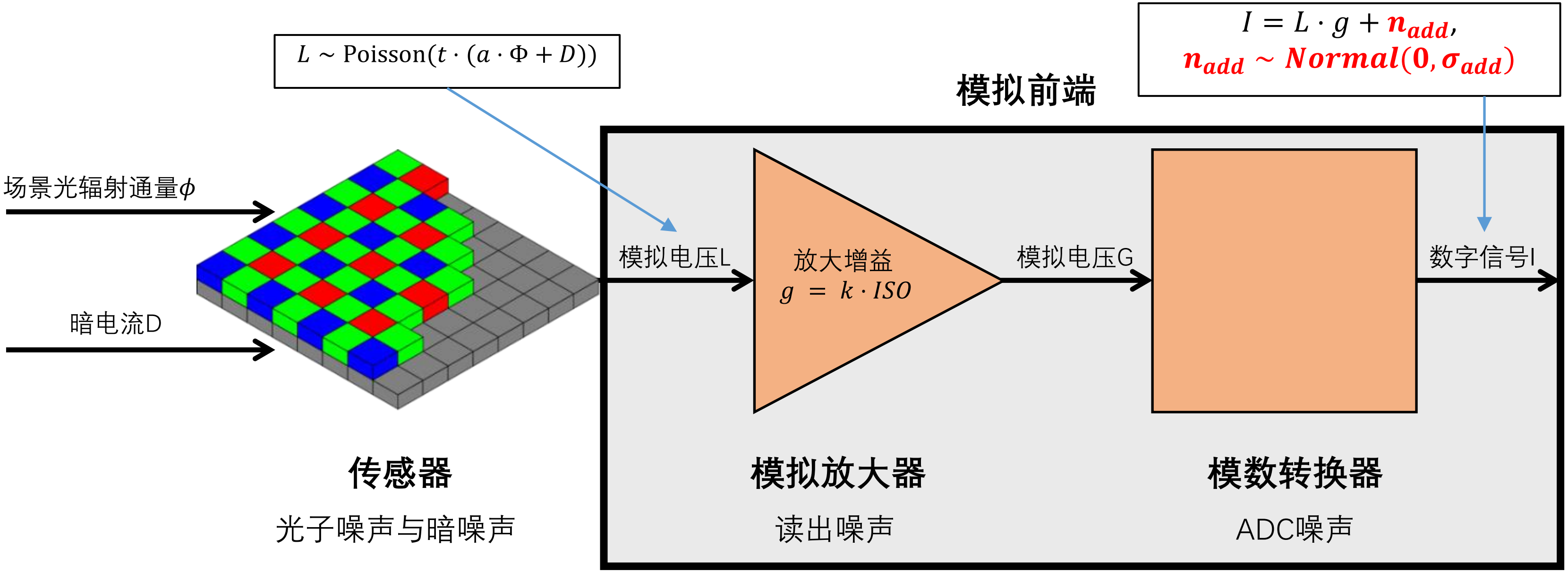
Yuzhi Wang[1,2], Haibin Huang[2], Qin Xu[2], Jiaming Liu[2], Yiqun Liu[1], and Jue Wang[2]

[1] Tsinghua University
[2] Megvii Technology

https://www.ecva.net/papers/eccv_2020/papers_ECCV/papers/123510001.pdf

课堂知识：仿射噪声模型

对于某个位置(x,y)的特定像素，其加性噪声可以通过加权平均该像素在多帧上的像素值来消除



考虑饱和时的像素亮度

$$I = \min(L \cdot g + n_{\text{add}}, I_{\max})$$

饱和阈值

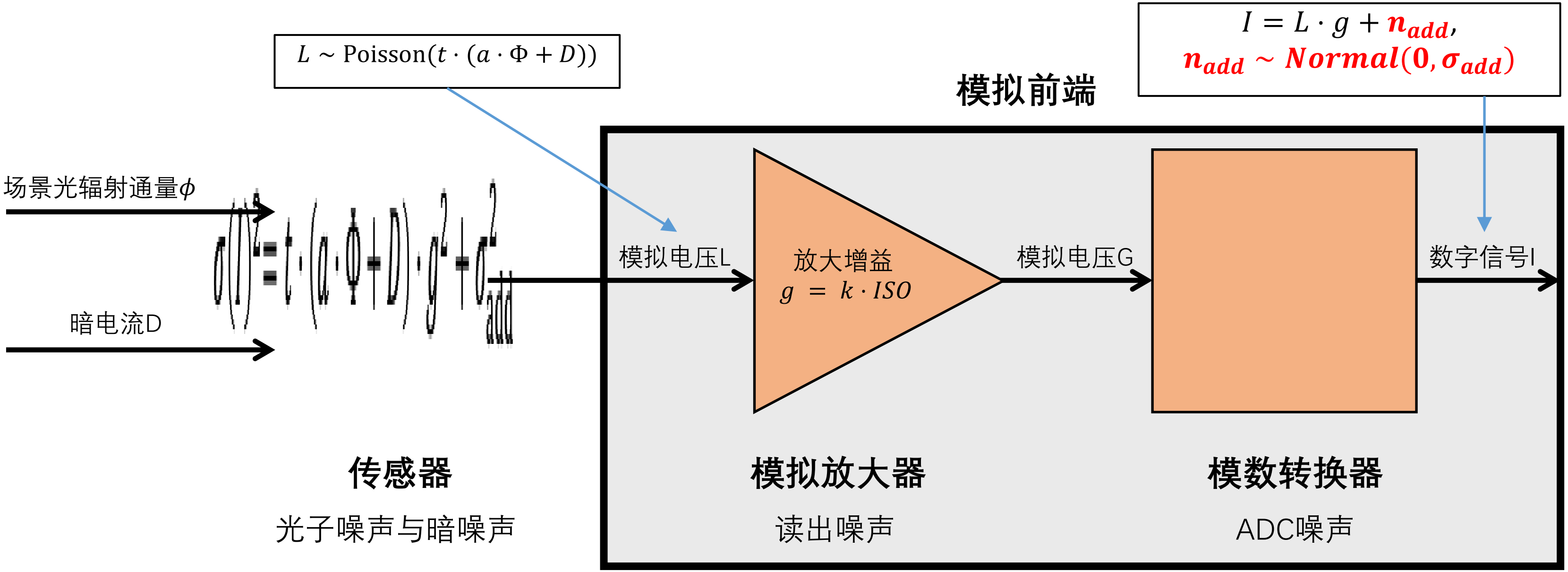
像素值的均值和方差(不考虑饱和)

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{add}}^2$$

课堂知识：仿射噪声模型

这种时域上的多帧加权平均，亦可用空域上的邻域加权平均来近似，其假设是一个局部邻域内的像素值具有相同的统计特征（包括均值和方差）



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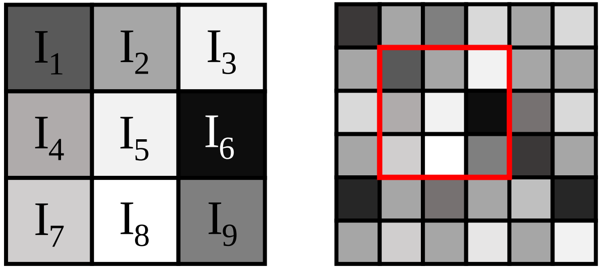
像素值的均值和方差(不考虑饱和)

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{add}}^2$$

原始的去噪

邻域插值（与去马赛克类似）



- 均值滤波

$$I'_5 = \frac{I_1 + I_2 + I_3 + I_4 + I_5 + I_6 + I_7 + I_8 + I_9}{9}$$

- 中值滤波

$$I'_5 = \text{median}(I_1, I_2, I_3, I_4, I_5, I_6, I_7, I_8, I_9)$$

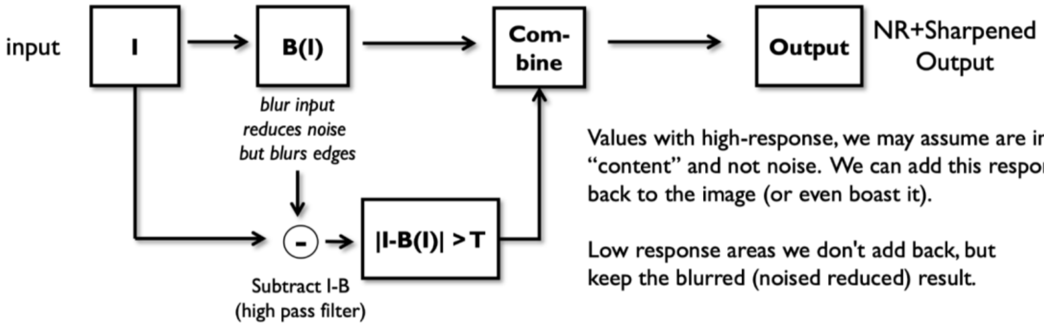
更多方法：高斯滤波、双边滤波等等

一个基本简单的去噪流程

A simple noise reduction approach

- Blur the image based on the ISO setting (higher ISO = more blur)
- Blurring will reduce noise, but also remove detail.
- Add image detail back for regions that have a high signal. We can even boost some parts of the signal to enhance detail (i.e. "sharpening")

Sketch of the procedure here

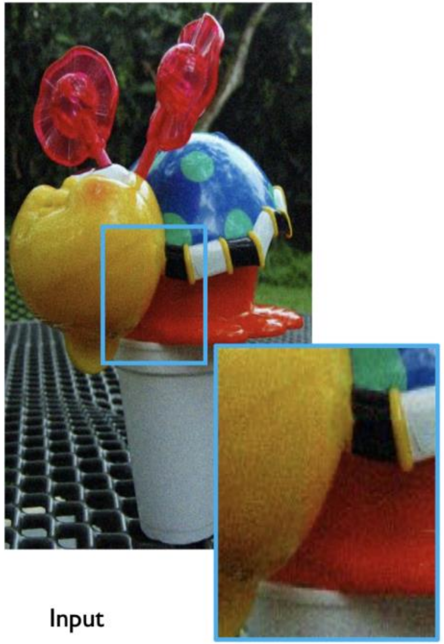


Values with high-response, we may assume are image “content” and not noise. We can add this response back to the image (or even boast it).

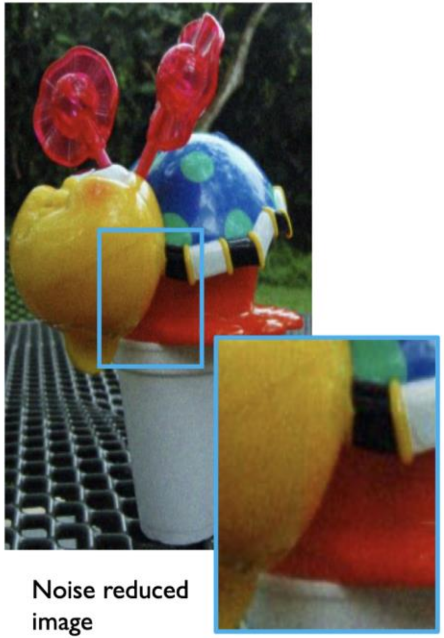
Low response areas we don't add back, but keep the blurred (noised reduced) result.

Noise Reduction

去噪效果



Input



Noise reduced image

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BM3D是非深度学习领域最经典最有效的去噪手段之一

Non-deep-learning noise reduction

- One of the best-performing methods was based on non-local means (2007).
- Block-matching with 3D filtering [BM3D]
- It is slow, but works well.

Dabov et al TIP'07

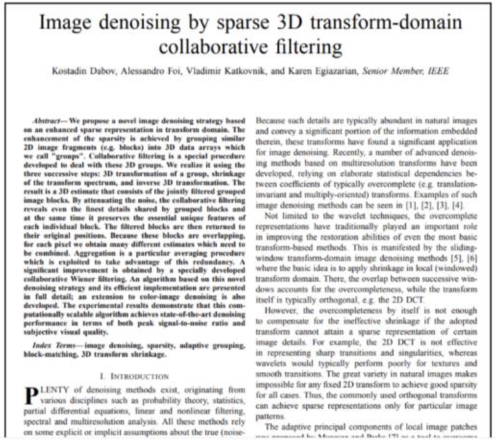


Image denoising by sparse 3D transform-domain collaborative filtering

Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian, *Senior Member, IEEE*

Abstract—We propose a novel image denoising strategy based on an enhanced sparse representation in transform domain. The enhancement of the sparsity is achieved by grouping similar 2D image fragments (e.g. blocks) into 3D data arrays which we call "groups". Collaborative filtering is a special procedure developed to deal with these 3D groups. We realize it using the three successive steps: 3D transformation of a group, shrinkage of the transform spectrum, and inverse 3D transformation. The result is a 3D estimate that consists of the jointly filtered grouped image blocks. By attenuating the noise, the collaborative filtering reveals even the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block. The filtered blocks are then returned to their original positions. Because these blocks are overlapping, for each pixel we obtain many different estimates which need to be combined. Aggregation is a particular averaging procedure which is exploited to take advantage of this redundancy. A significant improvement is obtained by a specially developed collaborative Wiener filtering. An algorithm based on this novel denoising strategy and its efficient implementation are presented in full detail; an extension to color-image denoising is also developed. The experimental results demonstrate that this computationally scalable algorithm achieves state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality.

Index Terms—image denoising, sparsity, adaptive grouping, block-matching, 3D transform shrinkage.

I. Introduction

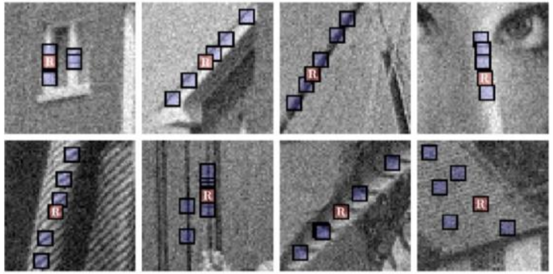
PLENTY of denoising methods exist, originating from various disciplines such as probability theory, statistics, partial differential equations, linear and nonlinear filtering, spectral and multiresolution analysis. All these methods rely on some explicit or implicit assumptions about the true (noise-

Because such details are typically abundant in natural images and convey a significant portion of the information embedded therein, these transforms have found a significant application for image denoising. Recently, a number of advanced denoising methods based on multiresolution transforms have been developed, relying on elaborate statistical dependencies between coefficients of typically overcomplete (e.g. translation-invariant and multiply-oriented) transforms. Examples of such image denoising methods can be seen in [1], [2], [3], [4].

Not limited to the wavelet techniques, the overcomplete representations have traditionally played an important role in improving the restoration abilities of even the most basic transform-based methods. This is manifested by the sliding-window transform-domain image denoising methods [5], [6] where the basic idea is to apply shrinkage in local (windowed) transform domain. There, the overlap between successive windows accounts for the overcompleteness, while the transform itself is typically orthogonal, e.g. the 2D DCT.

However, the overcompleteness by itself is not enough to compensate for the ineffective shrinkage if the adopted transform cannot attain a sparse representation of certain image details. For example, the 2D DCT is not effective in representing sharp transitions and singularities, whereas wavelets would typically perform poorly for textures and smooth transitions. The great variety in natural images makes impossible for any fixed 2D transform to achieve good sparsity for all cases. Thus, the commonly used orthogonal transforms can achieve sparse representations only for particular image patterns.

The adaptive principal components of local image patches

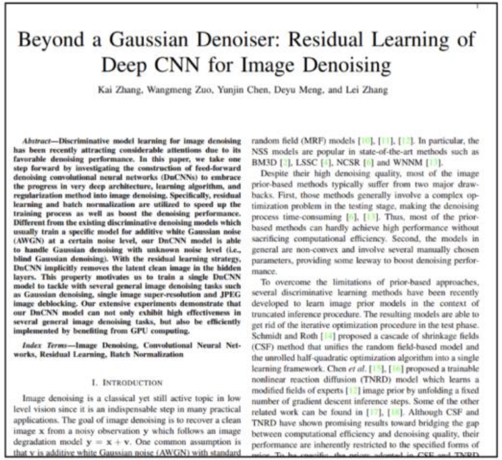


For small reference patch R, find similar patches.
Average the patches.

方法是对某个图像块，在图像上寻找和其相似的块堆叠成3D数据块，在这个3D数据块上进行滤波操作去除噪声

DNN for denoising (DnDNN)

Zhang et a. TIP'17



Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising

Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang

***Abstract*—Discriminative model learning for image denoising has been recently attracting considerable attentions due to its favorable denoising performance. In this paper, we take one step forward by investigating the construction of feed-forward denoising convolutional neural networks (DnCNNs) to embrace the progress in very deep architecture, learning algorithm, and regularization method into image denoising. Specifically, residual learning and batch normalization are utilized to speed up the training process as well as boost the denoising performance. Different from the existing discriminative denoising models which usually train a specific model for additive white Gaussian noise (AWGN) at a certain noise level, our DnCNN model is able to handle Gaussian denoising with unknown noise level (i.e., blind Gaussian denoising). With the residual learning strategy, DnCNN implicitly removes the latent clean image in the hidden layers. This property motivates us to train a single DnCNN model to tackle with several general image denoising tasks such as Gaussian denoising, single image super-resolution and JPEG image deblocking. Our extensive experiments demonstrate that our DnCNN model can not only exhibit high effectiveness in several general image denoising tasks, but also be efficiently implemented by benefiting from GPU computing.**

***Index Terms*—Image Denoising, Convolutional Neural Networks, Residual Learning, Batch Normalization**

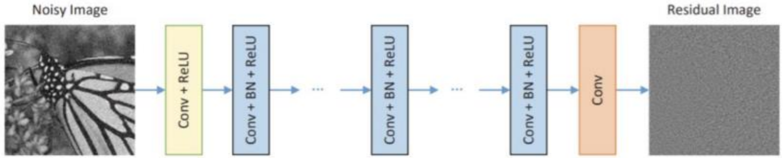
I. Introduction

Image denoising is a classical yet still active topic in low level vision since it is an indispensable step in many practical applications. The goal of image denoising is to recover a clean image $\mathbf{x}$ from a noisy observation $\mathbf{y}$ which follows an image degradation model $\mathbf{y} = \mathbf{x} + \mathbf{v}$. One common assumption is that $\mathbf{v}$ is additive white Gaussian noise (AWGN) with standard

random field (MRF) models [10], [11], [12]. In particular, the NSS models are popular in state-of-the-art methods such as BM3D [2], LSSC [4], NCSR [6] and WNNM [13].

Despite their high denoising quality, most of the image prior-based methods typically suffer from two major drawbacks. First, those methods generally involve a complex optimization problem in the testing stage, making the denoising process time-consuming [6], [13]. Thus, most of the prior-based methods can hardly achieve high performance without sacrificing computational efficiency. Second, the models in general are non-convex and involve several manually chosen parameters, providing some leeway to boost denoising performance.

To overcome the limitations of prior-based approaches, several discriminative learning methods have been recently developed to learn image prior models in the context of truncated inference procedure. The resulting models are able to get rid of the iterative optimization procedure in the test phase. Schmidt and Roth [14] proposed a cascade of shrinkage fields (CSF) method that unifies the random field-based model and the unrolled half-quadratic optimization algorithm into a single learning framework. Chen *et al.* [15], [16] proposed a trainable nonlinear reaction diffusion (TNRD) model which learns a modified fields of experts [12] image prior by unfolding a fixed number of gradient descent inference steps. Some of the other related work can be found in [17], [18]. Although CSF and TNRD have shown promising results toward bridging the gap between computational efficiency and denoising quality, their performance are inherently restricted to the specified forms of



- Straight-forward network based on deep residual learning (Kim SR-ResNet).
- Introduced batch normalization to the network.
- Predicts the residual noise layer.

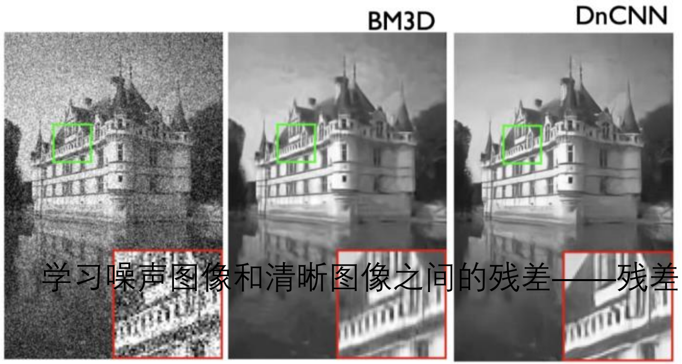
学习噪声图像和清晰图像之间的残差——残差即噪声

利用深度学习进行去噪的早期方法之一

DnCNN result

Methods	BM3D	WNNM	EPLL	MLP	CSF	TNRD	DnCNN-S	DnCNN-B
$\sigma = 15$	31.07	31.37	31.21	-	31.24	31.42	**31.73**	31.61
$\sigma = 25$	28.57	28.83	28.68	28.96	28.74	28.92	**29.23**	29.16
$\sigma = 50$	25.62	25.87	25.67	26.03	-	25.97	**26.23**	**26.23**

- Method trained on synthetic noise data.
- Beats BM3D and is much faster.
- BM3D does not require training data!



学习噪声图像和清晰图像之间的残差——残差即噪声

利用深度学习去噪的关键是高质量的训练和验证数据集

Need for real denoising dataset

Abdelhamed et al CVPR 2018

A High-Quality Denoising Dataset for Smartphone Cameras

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Stephen Lin, Microsoft Research, stevelin@microsoft.com
Michael S. Brown, York University, mbrown@eecs.yorku.ca

Abstract

The last decade has seen an astronomical shift from imaging with DSLR and point-and-shoot cameras to imaging with smartphone cameras. Due to the small aperture and sensor size, smartphone images have notably more noise than their DSLR counterparts. While denoising for smartphone images is an active research area, the research community currently lacks a denoising image dataset representative of real noisy images from smartphone cameras with high-quality ground truth. We address this issue in this paper with the following contributions. We propose a systematic procedure for estimating ground truth for noisy images that can be used to benchmark denoising performance for smartphone cameras. Using this procedure, we have captured a dataset – the Smartphone Image Denoising Dataset (SIDD) – of ~30,000 noisy images from 10 scenes under different lighting conditions using five representative smartphone cameras and generated their ground truth images. We used this dataset to benchmark a number of denoising algorithms. We show that CNN-based methods perform better when trained on our high-quality dataset than when trained using alternative strategies, such as low-ISO images used as a proxy for ground truth data.

(a) Noisy image (ISO 800) (b) Low-ISO image (ISO 100)
(c) Ground truth using [25] (d) Our ground truth

Figure 1: An example scene imaged with an LG *G4* smartphone camera: (a) a high-ISO noisy image; (b) same scene captured with low ISO – this type of image is often used as ground truth for (a); (c) ground truth estimated by [25]; (d) our ground truth. Noise estimates (β_1 and β_2 for noise level function and σ for Gaussian noise – see Section 3.2) indicate that our ground truth has significantly less noise than both (b) and (c). Images shown are processed in raw-RGB, while sRGB images are shown here to aid visualization.

dataset is essential both to focus attention on denoising of

SIDD: Smartphone Image Denoising Dataset

- -30,000 images
- -5 cameras
- -160 scene instances
- -15 ISO settings
- -Direct current lighting
- -Three illuminations

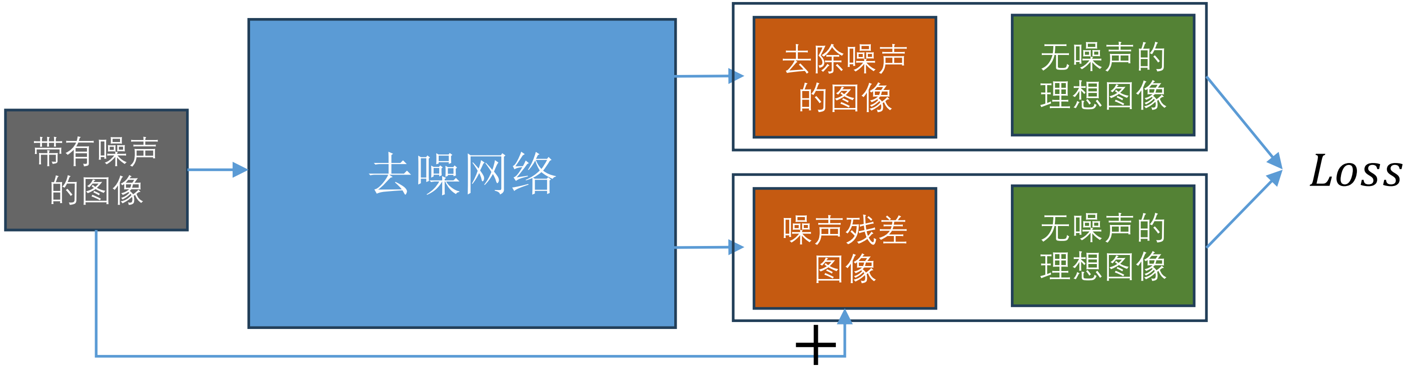
Interesting finding

- When trained on synthetic only, BM3D beat DnCNN
- When trained on real data, DnCNN wins
- Implies noise models in literature are not accurate

利用深度学习去噪的关键是高质量的训练和验证数据集

评价去噪算法优劣：比较（ 带有噪声的图像 ， 无噪声的理想图像 ） = 某种得分 (例如PSNR, SSIM等

训练去噪算法：



获取高质量数据集的两个思路

采集同一场景多帧含有噪声的图像集 → 高质量的去噪算法 → 去噪结果作为无噪声的理想图像

通过某种方式获取高信噪比的理想图像 → 为理想图像添加特定噪声 → 添加噪声后的图像作为含噪声的图像

SIDD：通过鲁棒的加权平均获取高质量的去噪图像数据集

Abdelhamed et al CVPR 2018

A High-Quality Denoising Dataset for Smartphone Cameras

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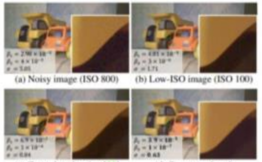

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Figure 1: An example scene imaged with an LG *G4* smartphone camera: (a) a high-ISO noisy image; (b) same scene captured with low ISO – this type of image is often used as ground truth for (a); (c) ground truth estimated by [25]; (d) our ground truth. Noise estimates (β_1 and β_2 for noise level function and σ for Gaussian noise – see Section 3.2) indicate that our ground truth has significantly less noise than both (b) and (c). Images shown are processed in raw-RGB, while sRGB images are shown here to aid visualization.

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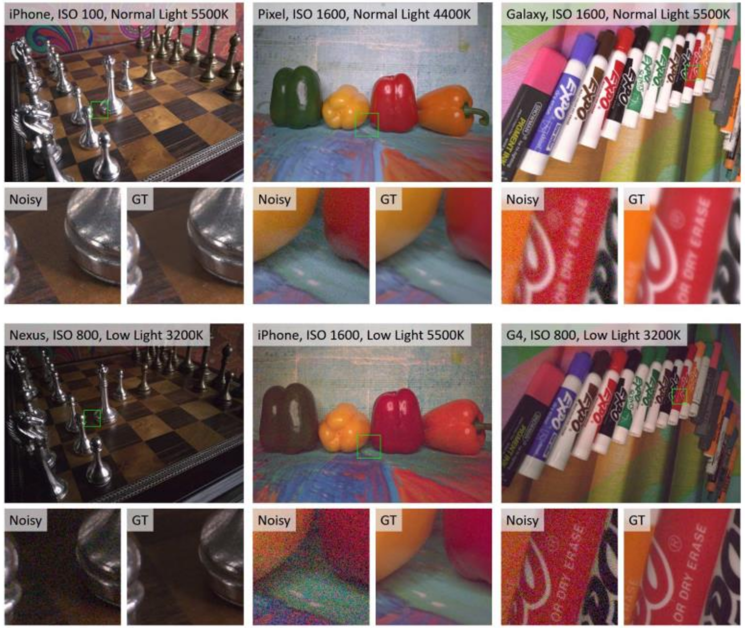

Figure 2: Examples of noisy images from our SIDD dataset captured under different lighting conditions and camera settings. Below each scene, zoomed-in regions from both the noisy image and our estimated ground truth (Section 4) are provided.

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SIDD：通过鲁棒的加权平均获取高质量的去噪图像数据集

- SIDD
  - 共拍摄30000张原始照片
    - 5个不同品牌型号的智能手机
    - 10个不同的场景
    - 4种不同成像设置的组合
      - ISO
      - 光源色温
      - 光源亮度
    - 上述每个组合150张图像

采集同一场景多帧含有噪声的图像集 → 高质量的去噪算法 → 去噪结果作为无噪声的理想图像

SIDD：通过鲁棒的加权平均获取高质量的去噪图像数据集

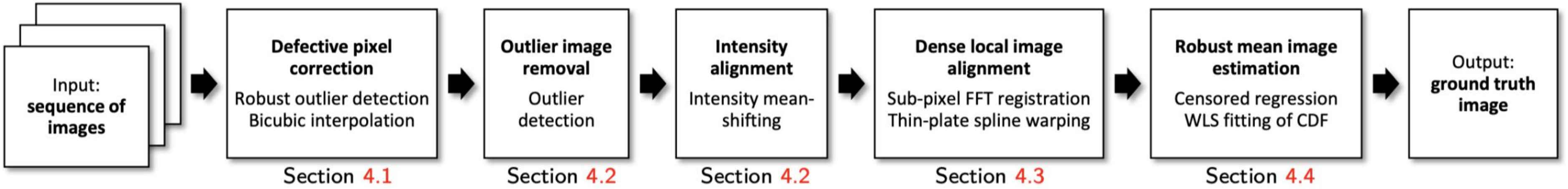

Figure 3: A block diagram illustrating the main steps in our procedure for ground truth image estimation. The respective sections for each step are shown.

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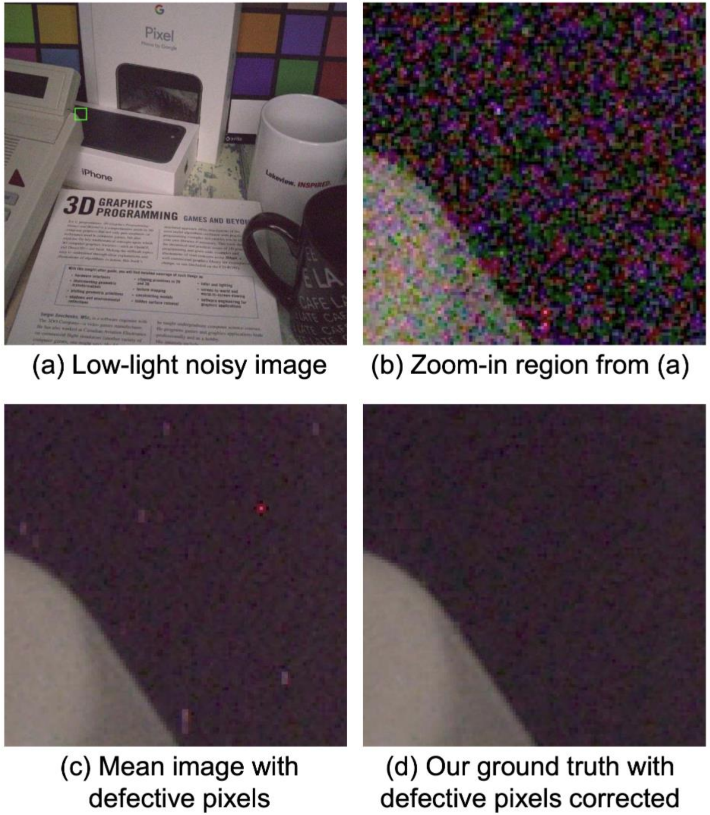
SIDD：鲁棒的坏点检测与修复算法

Defective pixel correction

Robust outlier detection
Bicubic interpolation



(a) Low-light noisy image
(b) Zoom-in region from (a)
(c) Mean image with defective pixels
(d) Our ground truth with defective pixels corrected

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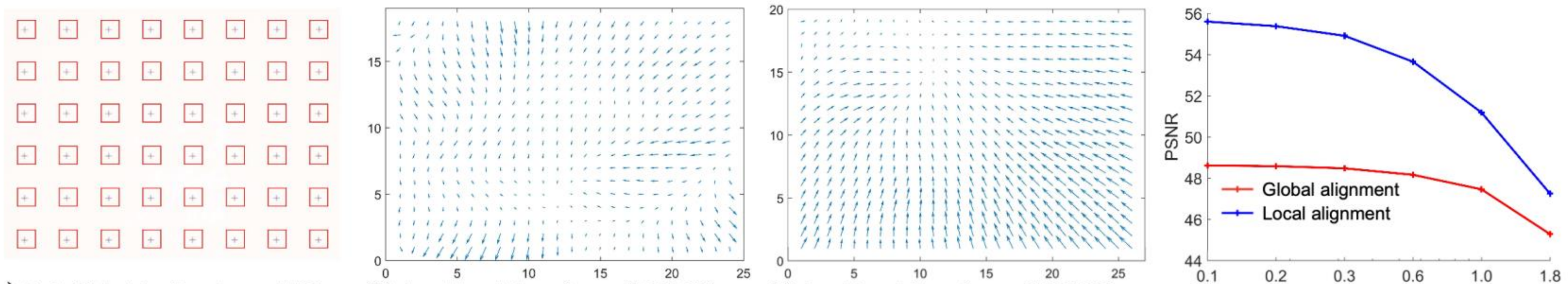
SIDD：稳定的亮度对齐与亚像素级别的空间对齐算法



(a) Part of fiducial pattern imaged 500 times by each camera on a vibration-controlled platform.

(b) Local translations (image #500/500)
Max. translation = 2.35 pixels
Apple iPhone 7

(c) Local translations (image #500/500)
Max. translation = 4.4 pixels
Google Pixel

(d)

Intensity alignment

Intensity mean-shifting

Section 4.2

Dense local image alignment

Sub-pixel FFT registration
Thin-plate spline warping

Section 4.3

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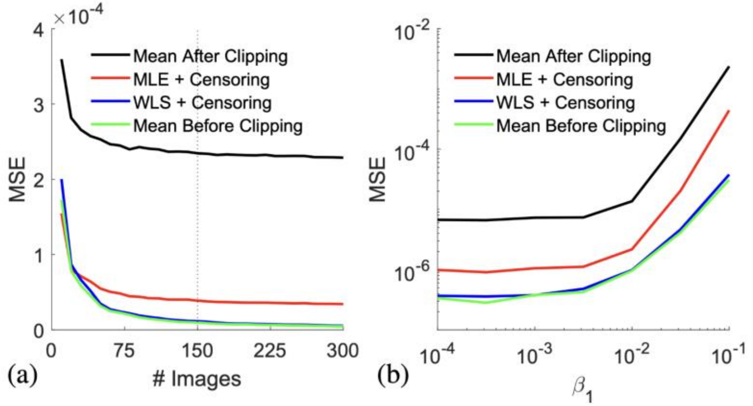

Robust mean image estimation

Censored regression
WLS fitting of CDF

Section 4.4

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SID: 利用长短曝光组成极暗场景增强数据集

Learning to See in the Dark

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Qifeng Chen
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Jia Xu
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(a) Camera output with ISO 8,000 (b) Camera output with ISO 409,600 (c) Our result from the raw data of (a)

Figure 1. Extreme low-light imaging with a convolutional network. Dark indoor environment. The illuminance at the camera is < 0.1 lux. The Sony α7S II sensor is exposed for 1/30 second. (a) Image produced by the camera with ISO 8,000. (b) Image produced by the camera with ISO 409,600. The image suffers from noise and color bias. (c) Image produced by our convolutional network applied to the raw sensor data from (a).

通过某种方式获取高信噪比的理想图像 → 为理想图像添加特定噪声 → 添加噪声后的图像作为含噪声的图像

课堂知识：传感器的信噪比

如果我们假设没有暗噪声的存在，信噪比和噪声大小分别为

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{t \cdot a \cdot \Phi \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2}$$

$$\sigma(I)^2 = t \cdot a \cdot \Phi \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2$$

如果曝光时间或场景的光辐射通量非常大呢?

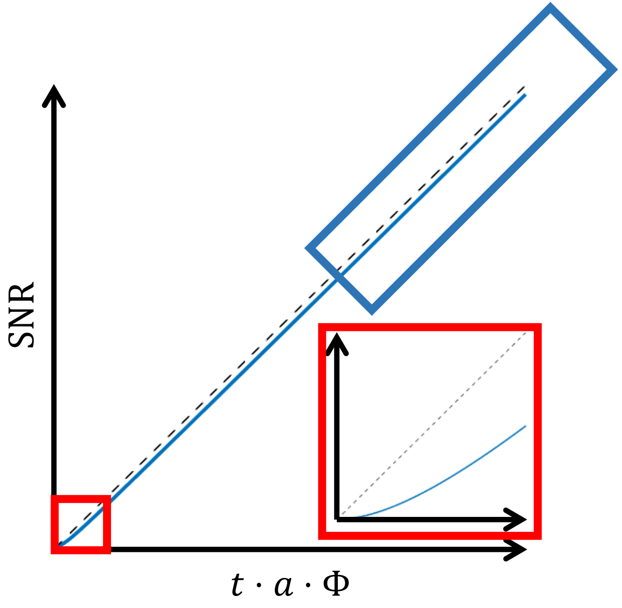
此时我们可以忽略加性噪声

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{t \cdot a \cdot \Phi \cdot g^2} = t \cdot a \cdot \Phi$$

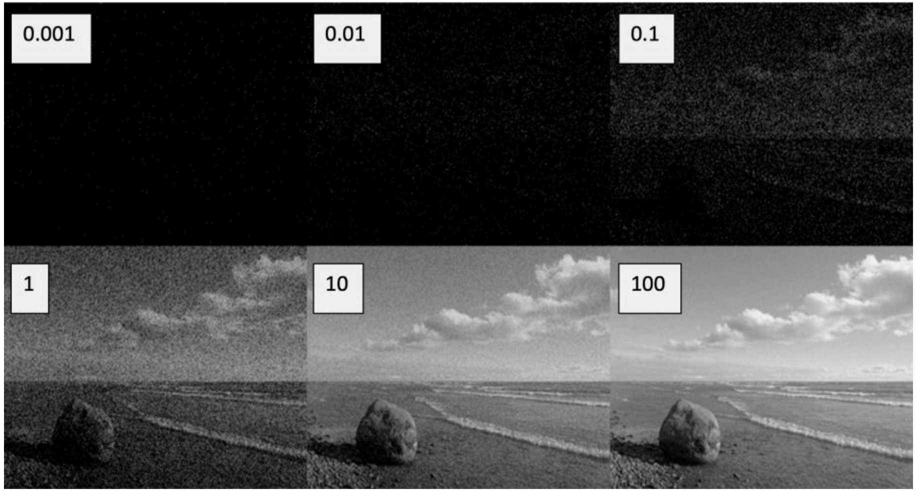
如果曝光时间或场景的光辐射通量非常小呢?

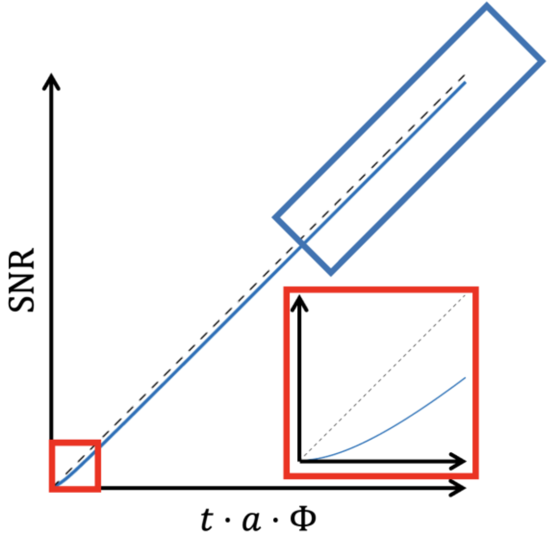
此时我们可以忽略场景相关的噪声

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{\sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2}$$



课堂知识：传感器的信噪比





当曝光时间加大或场景变亮

- 噪声的方差加大
- 信噪比提升

尽管噪声的绝对幅度增加了，但相对于我们测量的信号，其相对幅度减小了，所以我们看起来图像中的噪声降低了

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{t \cdot a \cdot \Phi \cdot g^2} = t \cdot a \cdot \Phi$$

注意如果我们加大曝光时间，我们需要仔细处理暗噪声

SID: 利用长短曝光组成极暗场景增强数据集

- SID
  - 拍摄数量和格式
    - 424个静态场景
      - 每个场景1张长曝光图像，存储为RAW格式以及对应的sRGB格式
      - 每个长曝光图像对应多张短曝光图像，总共5094张
  - 场景特征
    - 室外场景
      - 0.2Lux ~ 5 Lux，月光下或街灯下
    - 室内场景
      - 0.03Lux~0.3Lux, 灯光全光，仅保留非常微弱的间接光
  - 曝光时长
    - 短曝光
      - 1/30s ~ 1/10s
    - 长曝光
      - 100倍到300倍时长，约10s ~ 30s

SID: 利用长短曝光组成极暗场景增强数据集

Sony α7S II	Filter array	Exposure time (s)	# images
x300	Bayer	1/10, 1/30	1190
x250	Bayer	1/25	699
x100	Bayer	1/10	808
Fujifilm X-T2	**Filter array**	**Exposure time (s)**	**# images**
x300	X-Trans	1/30	630
x250	X-Trans	1/25	650
x100	X-Trans	1/10	1117

Table 1. The See-in-the-Dark (SID) dataset contains 5094 raw short-exposure images, each with a reference long-exposure image. The images were collected by two cameras (top and bottom). From left to right: ratio of exposure times between input and reference images, filter array, exposure time of input image, and number of images in each condition.

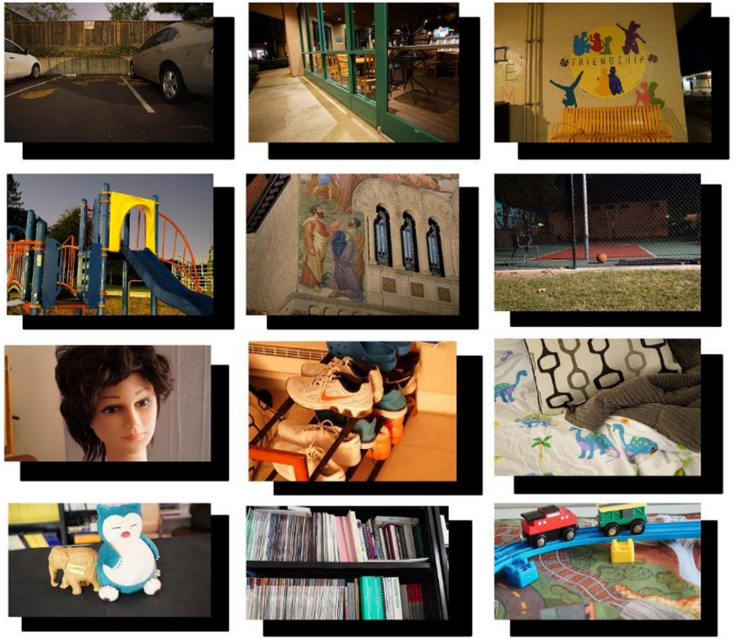
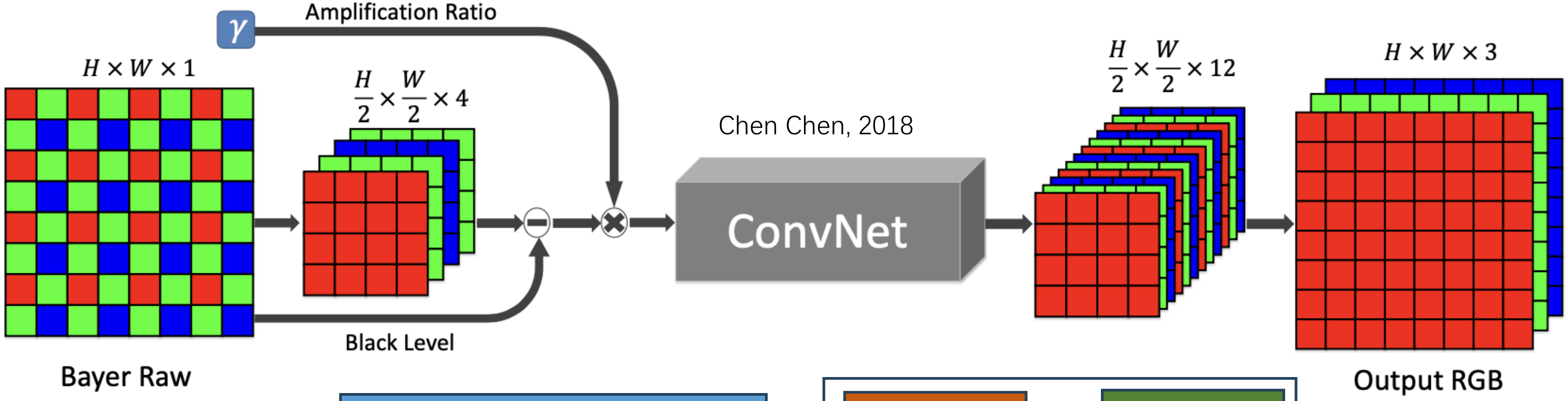
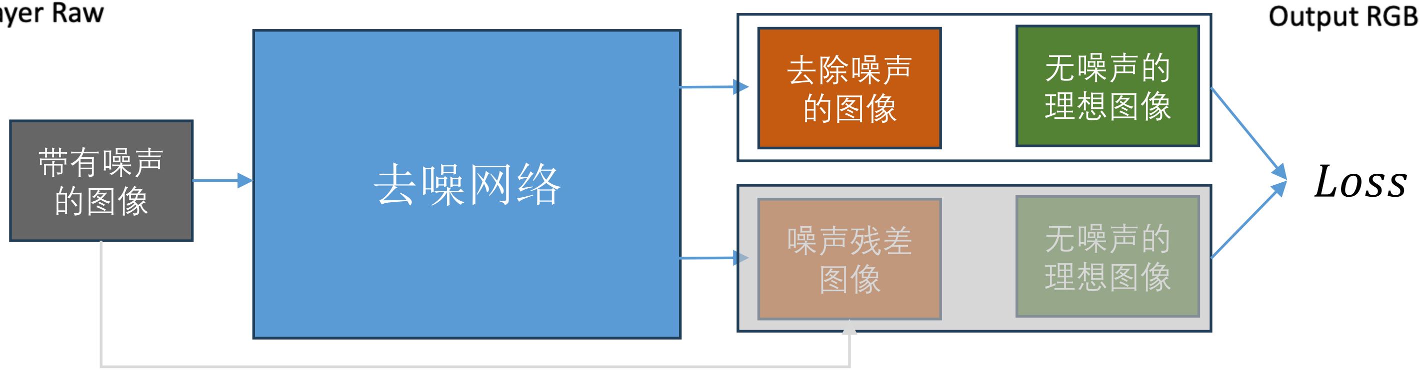


Figure 2. Example images in the SID dataset. Outdoor images in the top two rows, indoor images in the bottom rows. Long-exposure reference (ground truth) images are shown in front. Short-exposure input images (essentially black) are shown in the back. The illuminance at the camera is generally between 0.2 and 5 lux outdoors and between 0.03 and 0.3 lux indoors.

SID: 训练了一个直接的图像去噪网络来验证数据集的可用性





PDRID: 充分利用噪声模型合成噪声

Practical Deep Raw Image Denoising on Mobile Devices

Yuzhi Wang[1,2], Haibin Huang[2], Qin Xu[2], Jiaming Liu[2], Yiqun Liu[1], and Jue Wang[2]

[1] Tsinghua University
[2] Megvii Technology

(a) (b) (c) (d)

PDRID: 充分利用噪声模型合成噪声

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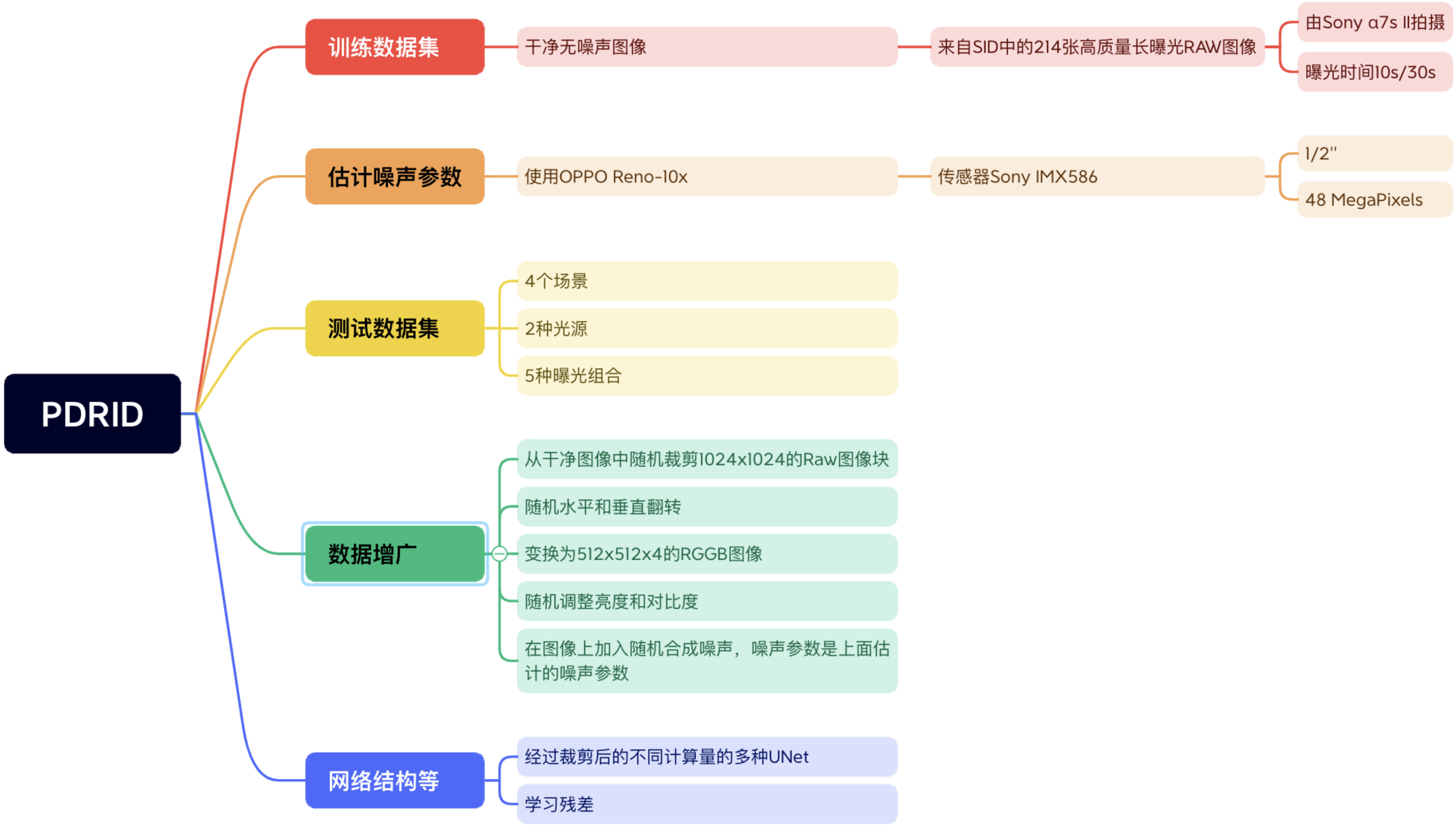
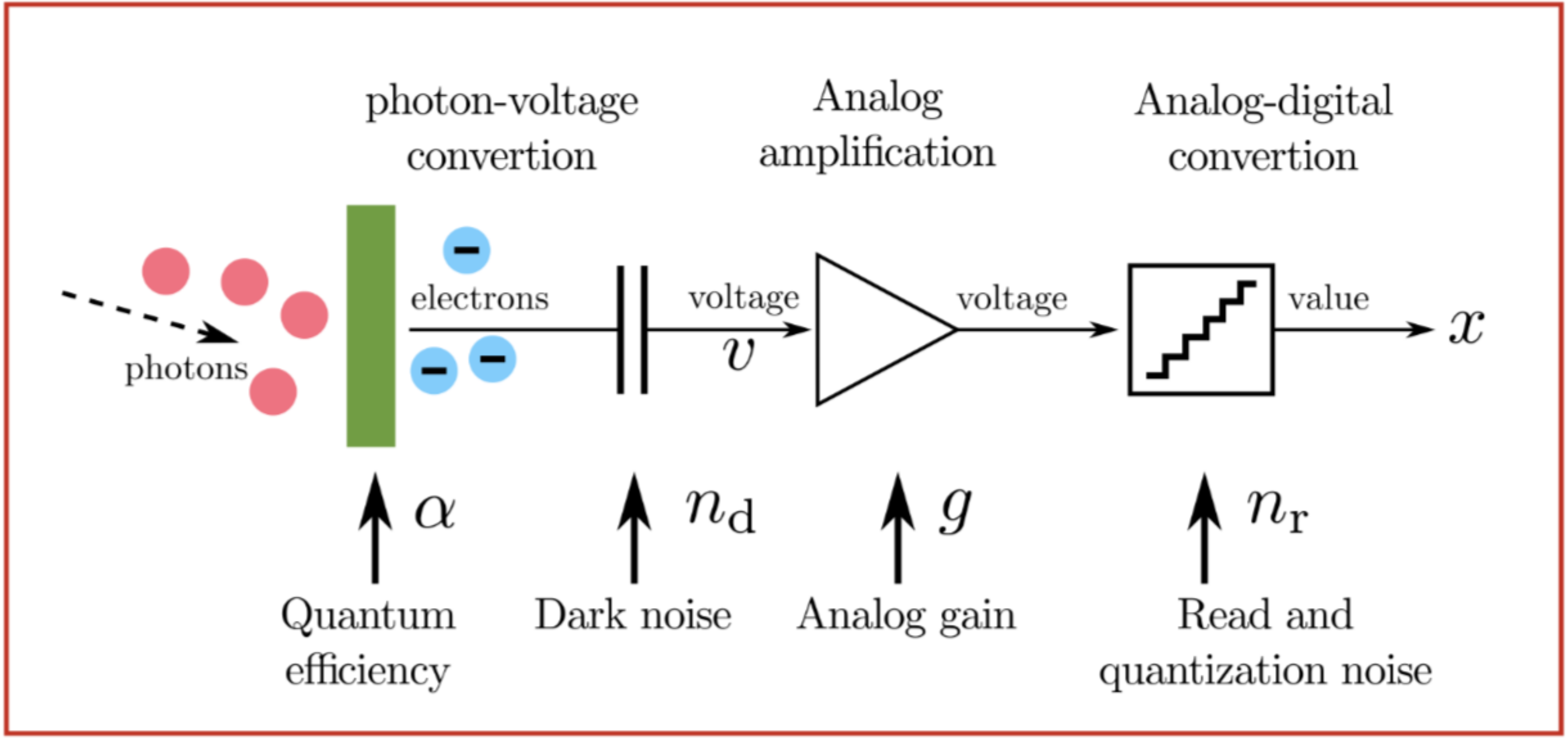
通过某种方式获取高信噪比的理想图像 → 为理想图像添加特定噪声 → 添加噪声后的图像作为含噪声的图像

PDRID: 充分利用噪声模型合成噪声



PDRID: 充分利用噪声模型合成噪声



PDRID: 噪声模型来自于EMVA标准1288

1288
EMVA Standard Compliant

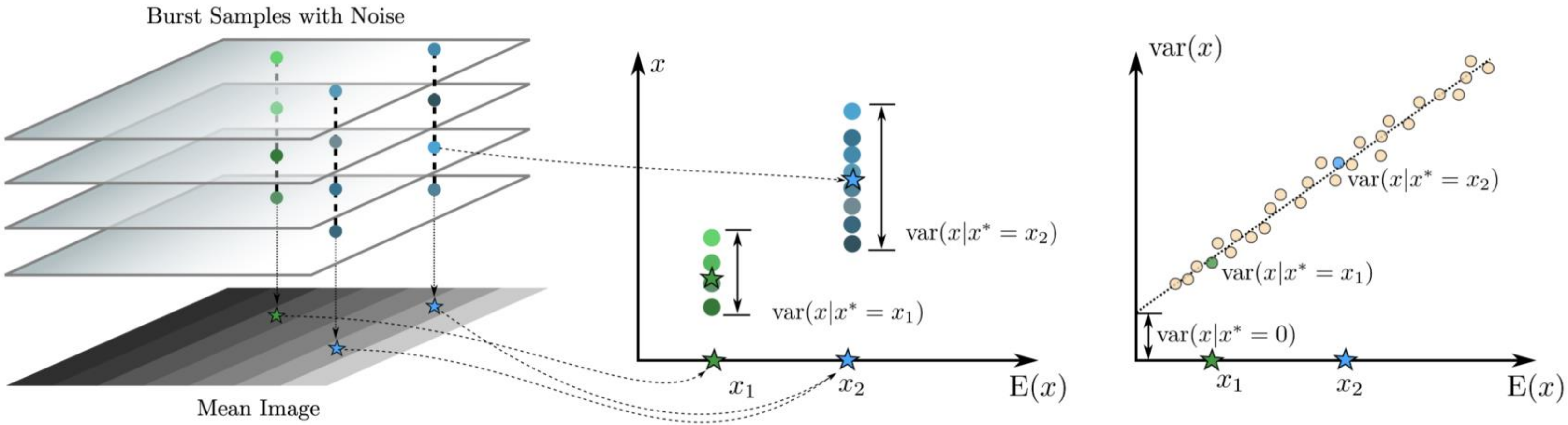
EMVA Standard 1288

Standard for Characterization of Image Sensors and Cameras

Release 3.0
November 29, 2010

Issued by
European Machine Vision Association
www.emva.org

PDRID: 估计噪声参数的方法——本质上是我们讲过的仿射噪声模型



(a) Noise Sampling (b) Noise Statistics (c) Param Estimation

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{add}}^2 = E(I)g + \sigma_{add}^2$$

PDRID: 去除增益g的影响，需要进一步估计g与噪声的关系

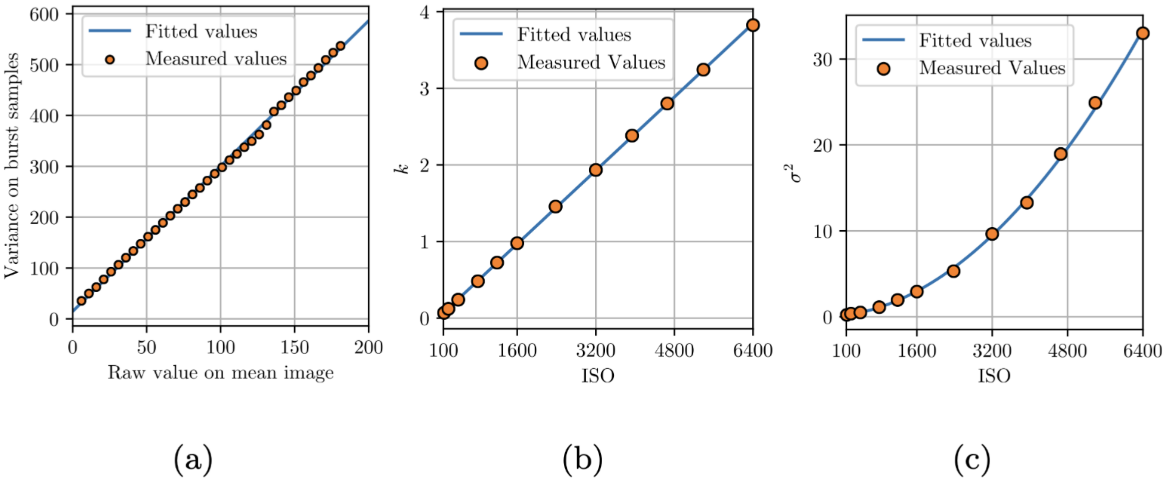


Fig. 6: Noise param estimation of Reno-10x smartphone: (a) parameter estimation at ISO-4800 (b) k values at different ISOs (c) σ^2 at differnt ISOs.

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{add}}^2 = E(I)g + \sigma_{add}^2$$

Yuzhi Wang, 2020

PDRID: 更小的计算量，更好的质量

选做作业：阅读PDRID论文3.1，3.2，5.1、5.2并完成合成噪声实验

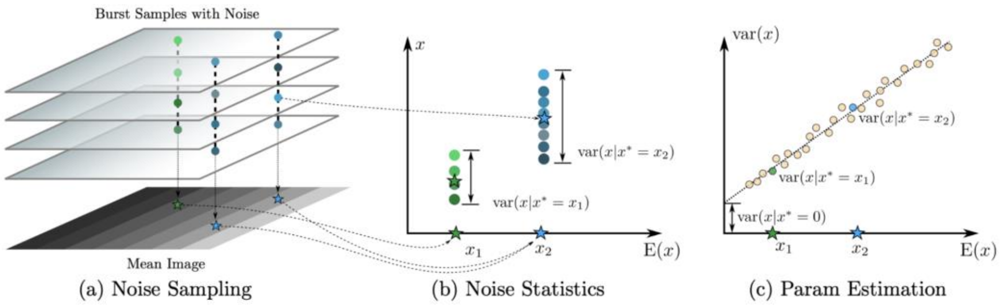


Fig. 3: Noise parameter estimation with a burst series of raw images of a static grayscale chart.

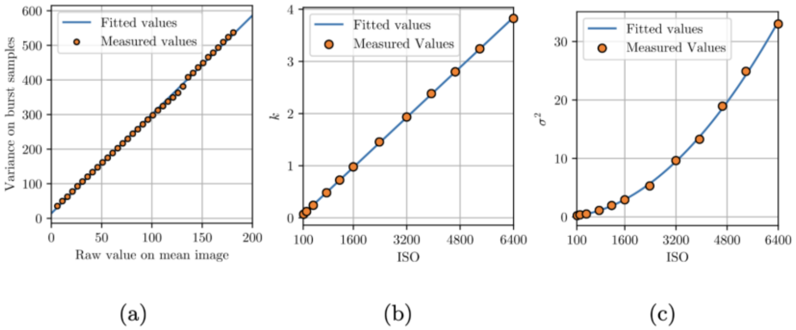
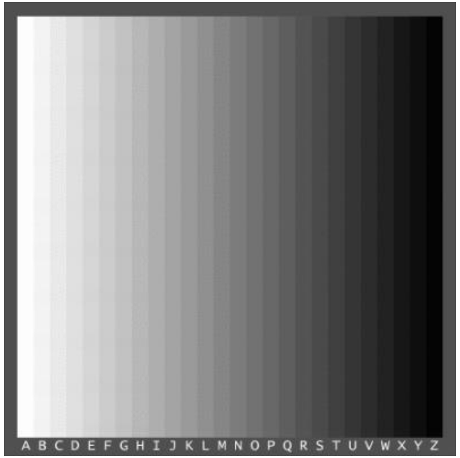
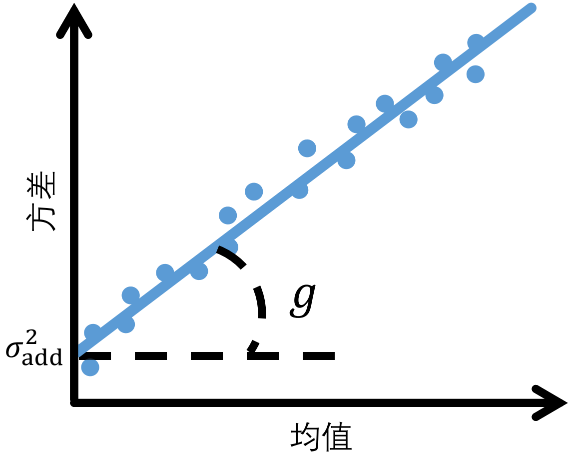


Fig. 6: Noise param estimation of Reno-10x smartphone: (a) parameter estimation at ISO-4800 (b) k values at different ISOs (c) σ^2 at diffrent ISOs.

课堂内容：估计增益g和加性噪声的方差σ_{add}

1. 拍摄大量灰阶卡的图像
2. 计算每个像素的经验均值和方差，然后绘制均值-方差图
3. 拟合一条直线，并使用斜率和截距来估算增益和方差





斜率

$$\sigma(I)^2 = E(I)\cdot g + \sigma_{\mathrm{add}}^2$$

截距

在不同的ISO设置(即不同的g)下重复上述实验(思考题)

选做作业：阅读PDRID论文3.1，3.2，5.1、5.2并完成合成噪声实验

1. 下载SID数据集
2. 选出至少1个场景的干净图像
3. 按照论文的方法，或课堂所讲授的方法，标定某个手机的噪声参数
4. 在上面选出的干净图像上添加以上述参数为基础的随机噪声，需要组合不同的增益
5. 观察你得到的图像，并做出分析

感谢聆听！

Thanks for Listening