NERDS: A GENERAL FRAMEWORK TO TRAIN CAMERA DENOISERS FROM SINGLE NOISY IMAGES

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ABSTRACT

We aim to train accurate denoising networks for smartphone/digital cameras from single noisy images. Downscaling is commonly used as a practical denoiser for low-resolution images. Based on this processing, we found that the pixel variance of the natural images is more robust to downscaling than the pixel variance of the camera noises. Intuitively, downscaling easily removes high-frequency noises than natural textures. To utilize this property, we can adopt noisy/clean image synthesis at low-resolution to train camera denoisers. On this basis, we propose a new solution pipeline – NERDS that estimates camera noises and synthesizes noisy-clean image pairs from only noisy images. In particular, it first models the noise in raw-sensor images as a Poisson-Gaussian distribution, then estimates the noise parameters using the difference of pixel variances by downscaling. We formulate the noise estimation as a gradient-descent-based optimization problem through a reparametrization trick. We further introduce a new Image Signal Processor (ISP) estimation method that enables denoiser training in a human-readable RGB space by transforming the synthetic raw images to the style of a given RGB noisy image. The noise and ISP estimations utilize rich augmentation to synthesize image pairs for the denoiser training. Experiments show that our NERDS can accurately train CNN-based denoisers (*e.g.*, DnCNN, ResNet-style network) outperforming previous noise-synthesis-based and self-supervision-based denoisers in real datasets.

1 INTRODUCTION

Image denoising is a conventional machine learning problem restoring original colors and patterns from noisy images. Deep-learning-based approaches have achieved breakthroughs in recent decades due to the power of neural networks. Early works (Zhang et al., 2017; Mao et al., 2016; Tai et al., 2017) have successfully removed additive white Gaussian noise (AWGN), which allows network training under supervision by synthesizing noisy-clean image pairs.

Nevertheless, denoising images captured by smartphone/digital cameras poses an obstacle, as it is difficult to obtain clean images for noisy images with the pixel-level alignment. Several works (Abdelhamed et al., 2018; Brummer & De Vleeschouwer, 2019) constructed datasets with the noisy-clean pairs for real-world images. Using these pairs (Figure 1(a)), many supervised-learning-based denoisers (Yue et al., 2019; Kim et al., 2020; Yue et al., 2020; Hu et al., 2021; Cheng et al., 2021) restore crisp images on benchmarks from the datasets. However, constructing such datasets requires tightly controlled capturing environments, complicated post-processing, and massive human labor.

To overcome the drawback of the plain supervised learning, two major types of researches have been studied. The first line of works synthesizes the realistic noise from clean images to utilize supervised denoiser training as visualized in Figure 1(b). Several approaches (Chen et al., 2018; Cha et al., 2021; Hong et al., 2020; Jang et al., 2021) adopt generative models using *unpaired* noisy-clean images based on GAN (Goodfellow et al., 2014), but they achieve limited accuracy on real noises. Some other works synthesize more realistic noises using existing noisy-clean image pairs (Zamir et al., 2020; Abdelhamed et al., 2019) or metadata for real cameras (Brooks et al., 2019; Guo et al., 2019), but they are limited in generalization for unseen noises. The second category aims to learn denoisers *without clean images*. The first work (Lehtinen et al., 2018) in this category proposed the learning framework using multiple noisy images. After that, many self-supervised-learning approaches (Batson & Royer, 2019; Krull et al., 2019; Byun et al., 2021) use single noisy

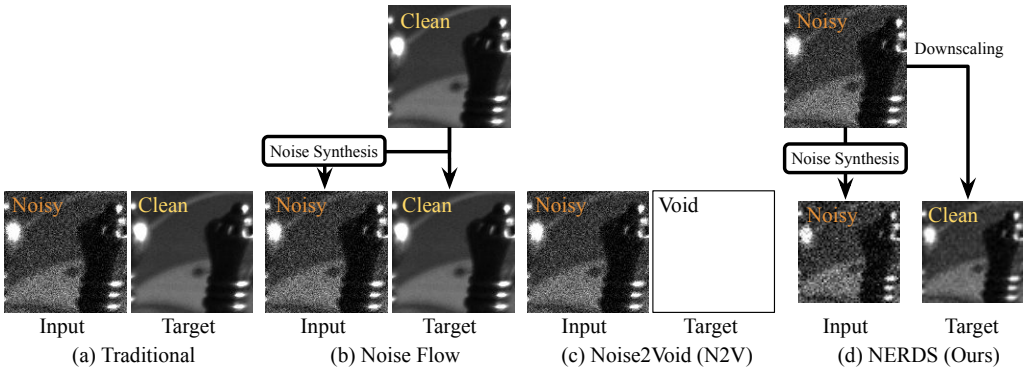

Figure 1: Different training schemes for CNN-based camera denoisers. (a) Traditionally, training denoisers requires pairs of noisy and clean images. However, clean target images are difficult to obtain from smartphone/digital cameras. (b) Noise Flow (Abdelhamed et al., 2019) generates realistic synthetic noise from clean images by learning the noise distributions using existing pairs of real images. (c) N2V (Krull et al., 2019) enables more practical training from single noisy images without clean targets, but requires custom network architectures. (d) Our NERDS synthesizes noisy-clean image pairs at low-resolution by utilizing image downscaling as a general denoiser and noise estimation through gradient-descent-based optimization. .

images (Figure 1(c)), which enable easy data collection and the denoiser adaptation to the test noises. However, they are still limited in real-world applications due to the requirements of custom network architectures and strong statistical noise assumptions.

To address the above limitations on camera denoiser training, we propose a new solution pipeline, namely NERDS, to perform noisy-clean image pair synthesis and accurate denoiser training from single noisy images. The framework composes three parts–noise estimation, ISP estimation, and denoiser training. We found that the pixel variance of natural clean images is robust to the image downscaling, which is a widely-used denoiser used for low-resolution images (Nah et al., 2019). The noise estimation adopts a Poisson-Gaussian noise model for the raw images from sensors and optimizes the noise parameters by the pixel variances of downscaled images. The downscaled images and the estimated noise parameters enable to synthesize noisy-clean image pairs at low-resolution (Figure 1(d)). Training denoisers on human-readable RGB images from real cameras has an other issue: the conversion from the raw images to the RGB images is a black box. Our ISP estimation enables the noise synthesis on the RGB space, by learning the RAW2RGB conversion using the raw-RGB image pairs[1]. Our denoiser training can utilize rich data augmentation based on estimated noise parameters and ISPs. Specifically, we introduce two techniques for this framework. First, a reparametrization trick allows to estimate noise parameters through a gradient-descent-based optimizer. Second, a technique for style disentanglement from raw-RGB noisy image pairs.

We summarize our contributions as follows:

- To the best of our knowledge, this is the first work to synthesize RGB noisy-clean image pairs at low-resolution for accurate camera denoiser training from single noisy images.
- We formulate noise estimation for Poisson-Gaussian noises as an optimization problem, and a novel reparameterization trick allows to estimate accurate noise parameters through gradient-descent.
- We propose a neural network that estimates the RAW2RGB conversions (or ISPs) used for given raw-RGB noisy image pairs. The ISP estimation generates realistic RGB noisy-clean image pairs from raw images.
- Our frameworks can train general CNN-based denoisers (*e.g.* DnCNN, ResNet-style network) accurately for given test noisy images by performing noise synthesis using them.

[1]Major camera manufacturers (*e.g.*, Samsung, Apple, Xiaomi, Cannon, and Sonny) provide raw and RGB image pairs on their devices.

2 RELATED WORKS

2.1 BLIND IMAGE DENOISING

Traditional methods Classical methods usually denoise noisy images without training data using wavelet (Donoho & Johnstone, 1995), filtering (Buades et al., 2005) including BM3D (Dabov et al., 2007), optimization (Elad & Aharon, 2006; Mairal et al., 2009; Gu et al., 2014), and effective prior (Zoran & Weiss, 2011). However, they perform limited accuracy compared to the recent deep-learning-based approaches.

Supervised-learning-based methods SIDD (Abdelhamed et al., 2018) and NIND (Brummer & De Vleeschouwer, 2019) captured real noisy-clean image pairs to enable supervised-learning for real camera denoisers. However, the capturing procedure is unacceptably expensive and cumbersome. We describe the literature of realistic noise synthesis methods for the supervised-learning. DnCNN (Zhang et al., 2017) introduced a neural network to remove additive white Gaussian noise (AWGN) for the first time. However, Guo *et al.* (Guo et al., 2019) demonstrated the limitation of AWGN denoisers to signal-dependent or spatially-correlated noises, which are known as the characteristics of real-world images. To alleviate this problem, two lines of works have been researched. The first category uses generative models for noise synthesis with stable learning (Chen et al., 2018), various noise characteristics (Jang et al., 2021), knowledge distillation (Wu et al., 2020), self-supervised-learning (Cha et al., 2021), and conditional adversarial networks (Hong et al., 2020). Nevertheless, the scene statistics mismatched between clean and noisy datasets make it difficult to train accurate denoisers in practice.

The second category investigates camera noise modeling. CBDNet (Guo et al., 2019) transforms AWGN to realistic noise by using signal-dependent noise parameters and simulating in-camera ISP functions, such as gamma correction and demosaicing. UPI (Brooks et al., 2019) converts RGB images to raw images and simulates noises using metadata of specific cameras. CycleISP (Zamir et al., 2020) trains neural networks for both RAW2RGB and RGB2RAW conversions on large-scale datasets with specific ISP and noise settings. Noise Flow (Abdelhamed et al., 2019) synthesizes raw noisy images using normalizing flow and metadata. The work on (Chang et al., 2020) proposed a GAN-based framework for noise generation in raw images which is adaptive to camera. In (Zhang et al., 2021), the authors claimed that the noise levels in metadata are inaccurate. Recently, the method in (Kousha et al., 2022) models the sRGB noise distribution using normalizing flow. SCUNet (Zhang et al., 2022) proposed a practical noise model for a general-purpose denoiser.

However, all above methods require real noisy-clean image pairs, ISPs, metadata, or high-quality clean images which are not always available. More importantly, the noise synthesis using predetermined training datasets leads poor denoising performances on unseen noises. In contrast, the proposed method (NERDS) synthesizes realistic noisy-clean image pairs from only noisy images, that enable accurate denoiser training specialized in the test images.

Self-supervised-learning-based methods Noise2Noise (Lehtinen et al., 2018) introduced a framework that trains denoiers using noisy images *only* for the first time. Noise2Void (Krull et al., 2019), Noise2Self (Batson & Royer, 2019), Noise2Same (Xie et al., 2020), and Neighbor2Neighbor (Huang et al., 2021) adopted advanced approaches which can train denoisers with single images corrupted by the i.i.d noise. Noisier2Noise (Moran et al., 2020), NAC (Xu et al., 2020), and R2R (Pang et al., 2021) add additive noises to the given noisy images to make auxiliary training pairs by using prior knowledge (or assumptions) of the noise distribution. Notably, the blind-spot network (BSN) in (Krull et al., 2019) has been improved by efficient architectures with small receptive fields (Laine et al., 2019) and dilated convolutions (Wu et al., 2020). Using the advanced BSNs, FBI-D (Byun et al., 2021) adopts a denoiser specialized in Poisson-Gaussian noise for real-world raw image denoising. AP-BSN (Wooseok Lee, 2022) breaks the spatially-correlated noise of real-world RGB images by pixel-shuffle downsampling.

Although above self-supervised-learning methods use practical training datasets (only noisy images), they require custom network architectures or strong noise assumptions. In contrast, NERDS performs noise synthesis that allows to train general CNN-based denoisers based on the general noise modeling for smartphone/digital cameras.

2.2 NOISE ESTIMATION

Prior knowledge of the noise distribution supports accurate restoration in most methods for image denoising, but it is not generally available in practice. Noise estimation methods alleviate this problem, especially for the additive white Gaussian noise (AWGN) and the Poisson-Gaussian noise. Principal component analysis (PCA) based approaches (Liu et al., 2013; Pyatykh et al., 2012; Chen et al., 2015) perform accurate AWGN estimation. For the Poisson-Gaussian noise model, most existing methods (Abramov et al., 2010; Uss et al., 2013) including (Foi et al., 2008; Liu et al., 2014) adopt two step approaches; estimating the local means and variances, then adopting maximum likelihood estimation (MLE) to fit the noise model. Foi *et al.*(Foi et al., 2008) proposed the Poisson-Gaussian noise model for the first time and an noise estimation algorithm based on wavelet decomposition. Liu *et al.* (Liu et al., 2014) adopted iterative patch selection for the generalized source-dependent noise. Recently, PGE-Net (Byun et al., 2021) adopts neural networks for accurate and fast optimization based on Generalized Anscombe Transformation (GAT) (Anscombe, 1948). In contrast, we proposed a noise estimation method for Poisson-Gaussian noise using natural scene statistics with gradient-descent-based optimization.

3 PRELIMINARY: NOISE MODELING

In a digital camera, an image sensor converts light into a digital signal (or a raw image), and an image signal processor (ISP) converts it into a human-readable RGB image. We regard that the noise of RGB images originates from the image sensor and is transformed by the ISP. Thus, we model the noise distribution of raw images and the RAW2RGB conversion including ISPs.

Raw Image: Poisson-Gaussian (P-G) Noise A common noise model for raw images follows the Poisson-Gaussian distribution (Foi et al., 2008), defined as:

$$\boldsymbol{x} \sim \mathcal{N}(\boldsymbol{z}, \beta_1^2 \boldsymbol{z} + \beta_2^2), \tag{1}$$

which is a heteroscedastic Gaussian where $\boldsymbol{z}$ is the true signal, $\boldsymbol{x}$ is a raw noisy image observed on real image sensors, and β_1, $\beta_2 \geq 0$ are signal-dependent and signal-independent noise parameters. Real cameras provide $\boldsymbol{x}$ as well as β_1 and β_2 in metadata. However, the noise parameters in the metadata are often inaccurate (Zhang et al., 2021).

RGB Image: Transformed Noise ISPs transform raw images into RGB images using nonlinear functions, such as demosaicing, white balancing, color correction, and tone mapping. The transformation changes the noise distribution, such as breaking the i.i.d property in equation 1. Moreover, users can retouch image tones and colors, altering the noise distribution further. We define the such RAW2RGB conversion ($\boldsymbol{T}$) as a function of the image style ($\boldsymbol{s}$),

$$\boldsymbol{y} \equiv T(\boldsymbol{x}; \boldsymbol{s}), \tag{2}$$

where $\boldsymbol{x}$ is a raw noisy image obtained from real image sensors and $\boldsymbol{y}$ is the RGB noisy image with custom tones and colors. The real noise datasets (Abdelhamed et al., 2018; Plotz & Roth, 2017) used a simple and open-source ISP for the entire dataset without any image retouching processes. However, modern smartphones and digital cameras use custom ISPs with hidden internal functions. They provide multiple image styles depending on the scenes with user edits.

The following section provides a general framework to estimate P-G noise parameters (β_1, β_2), the RAW2RGB conversion ($\boldsymbol{T}$), and the image style ($\boldsymbol{s}$) using only noisy images ($\boldsymbol{x}$, $\boldsymbol{y}$).

4 PROPOSED METHOD

4.1 OVERVIEW

For a given noisy pair of raw ($\boldsymbol{x}$) and RGB ($\boldsymbol{y}$) images, the proposed method composes three steps to restore the clean RGB image without auxiliary training data. First, we estimate noise parameters (β_1, β_2) from $\boldsymbol{x}$ (Section 4.3). Second, we learn the conversion from $\boldsymbol{x}$ to $\boldsymbol{y}$ while disentangling the image style $\boldsymbol{s}$ (Section 4.4). Third, we synthesize diverse pairs of noisy-clean images to train arbitrary RGB denoisers with a general supervised-learning framework (Section 4.5).

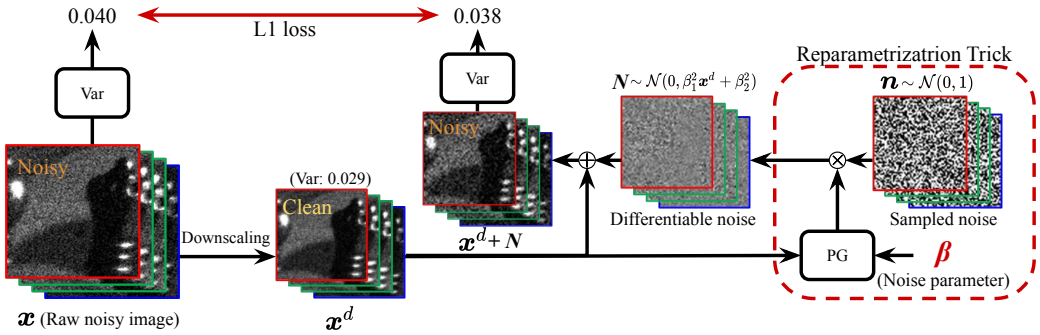

Figure 2: Noise estimation from a raw noisy image with a reparametrization trick. .

4.2 Observation

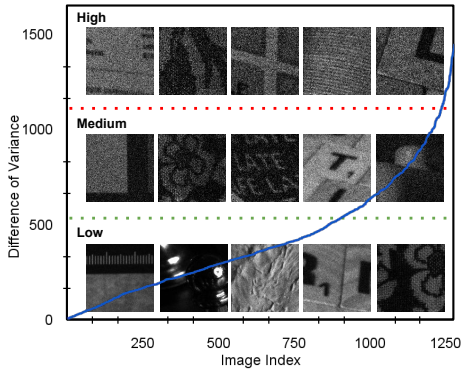

Figure 3: The ranked curve for the difference of pixel variances through downscaling on images from SIDD validation set and the visualization of noise levels.

We first illustrate our observation on raw noisy images with downscaling. Specifically, we investigate the statistical characteristics variances of 256×256 images in SIDD validation dataset (Abdelhamed et al., 2018). To evaluate their noise levels, we downscale all raw images for each color channel with the scaling factor of 2, and rank these images according to the differences of pixel variances through downscaling. As visualized in Figure 3, we show these values in a blue curve and separate them into three levels –low, medium, high. It is observed that the images with high differences are very noisy, while the images with low differences present clean textures. This phenomenon indicates that the true signal $\boldsymbol{z}$ is robust to the pixel variances through downscaling than real noises. That is why we propose the following method, which uses downscaled images and pixel variances to estimate noise parameters of original images.

4.3 Poisson-Gaussian Noise Estimation via A Reparameterization Trick

We aim to estimate noise for $\boldsymbol{x}$ without any information other than $\boldsymbol{x}$. For this, we find an additive noise ($\boldsymbol{N}$) for the downscaled image ($\boldsymbol{x}^d$) by solving the following optimization problem,

$$\min_{\boldsymbol{N}} |Var(\boldsymbol{x}) - Var(\boldsymbol{x}^d + \boldsymbol{N})|, \tag{3}$$

where $\boldsymbol{N} \sim \mathcal{N}(0, \beta_1^2 \boldsymbol{x}^d + \beta_2^2)$ is the Poisson-Gaussian noise discussed in equation 1 and $Var(\cdot)$ denotes a function that outputs the pixel variance of the input image. We can approximate β_1 and β_2 as the noise parameters for $\boldsymbol{x}$, given that downscaling reduces noise levels and that the pixel variance of an image is correlated with the variance of the noise distribution, as discussed in Section 4.2. The Appendix analyzes the downscaling effect further. However, equation 3 is difficult to optimize due to the non-differentiable process of noise sampling. To alleviate this problem, we introduce a reparameterization trick that separates the noise sampling into learnable parameters and the sampling from the normal distribution. Formally, we reformulate equation 3 as

$$\min_{\boldsymbol{\beta}} |Var(\boldsymbol{x}) - Var(\boldsymbol{x}^d + PG(\boldsymbol{\beta}, \boldsymbol{x}^d) \times \boldsymbol{n})|, \tag{4}$$

where $PG(\boldsymbol{\beta}, \boldsymbol{x}^d) = (\beta_1^2 \boldsymbol{x}^d + \beta_2^2)^{0.5}$ denotes Poisson-Gaussian converter and $\boldsymbol{n} \sim \mathcal{N}(0, 1)$ is the additive noise with the normal distribution. Given that the only learnable parameters in equation 4 are β_1 and β_2, a gradient-descent optimizer (*e.g.*, Adam (Kingma & Ba, 2015)) easily finds the noise parameters. Figure 2 visualizes the optimization problem used as noise estimation for $\boldsymbol{x}$.

We are surprised that such a simple optimization problem estimates accurate noise parameters, while downscaled images can contain remaining noise or over-smoothing textures. This result is because

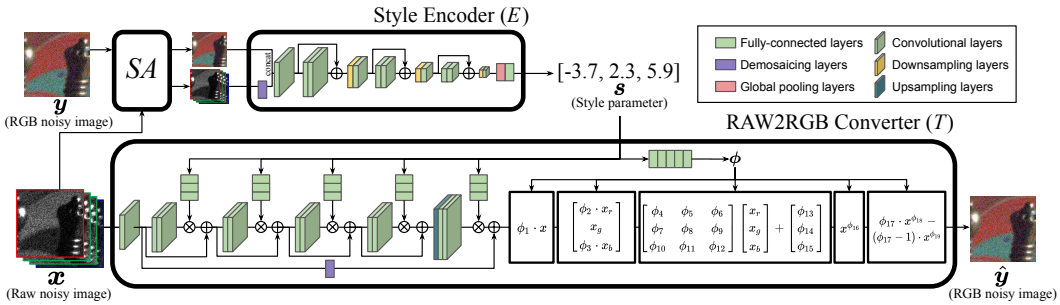

Figure 4: ISP estimation from a pair of raw-RGB noisy images with style disentanglement.

the well-designed optimizer learns the characteristics of signal-dependent and signal-independent noises over the entire image content.

So far we have discussed noise estimation and synthesis on raw images. For more practical applications, the following section describes RGB noise synthesis by estimating RAW2RGB conversion.

4.4 ISP Estimation with Style Disentanglement

We aim to learn a RAW2RGB conversion (or an ISP) from $\boldsymbol{x}$ to $\boldsymbol{y}$. However, a naìve network training from $\boldsymbol{x}$ to $\boldsymbol{y}$ can easily overfit to the image contents. Moreover, to generate multiple styles of RGB images, training a neural network for each style is resource intensive. For this, we disentangle the styles from RGB images, allowing a network to learn multiple-style generation.

Specifically, our ISP estimation composes two networks, the style encoder (E) and the RAW2RGB converter (T) (Figure 4). E identifies the image style as a style parameter ($\boldsymbol{s}$) from the raw noisy image ($\boldsymbol{x}$) and the RGB noisy image ($\boldsymbol{y}$) while T uses $\boldsymbol{x}$ and $\boldsymbol{s}$ as input to generate an RGB image ($\hat{\boldsymbol{y}}$). Then, we can recall the equation equation 2 as

$$\hat{\boldsymbol{y}} = T(\boldsymbol{x}; E(\boldsymbol{x}, \boldsymbol{y})), \tag{5}$$

where $\boldsymbol{s} = E(\boldsymbol{x}, \boldsymbol{y})$ while training E and T to minimize the L1 difference between $\hat{\boldsymbol{y}}$ and $\boldsymbol{y}$. E composes 6 residual blocks, global pooling, and a fully connected layer and T composes 4 residual blocks and the parameterized ISP functions (Kim & Lee, 2022). We use the residual blocks of two convolutional layers and one ReLU activation with 64 filters and 3×3 kernels. The training data can compose a single pair or multiple pairs of raw-RGB noisy images. To avoid learning identity mapping from the input $\boldsymbol{y}$ to the output $\hat{\boldsymbol{y}}$, we first adopt image scale augmentation (SA) that changes the image resolution. Each scaling factor transforms the noise of $\boldsymbol{x}$ and $\boldsymbol{y}$ while SA randomly samples the scaling factor to prevent the encoder from learning noises. Formally, we redefine the style parameter ($\boldsymbol{s}$) as follows,

$$\boldsymbol{s} \equiv E(SA(\boldsymbol{x}, \boldsymbol{y})). \tag{6}$$

Second, we design a bottleneck structure that lowers the dimension of $\boldsymbol{s}$ to avoid encoding of information about image contents. E reduces channels and resolutions of $\boldsymbol{s}$ ($\boldsymbol{s} \in \mathbb{R}^{3\times1\times1}$ in this paper). $\boldsymbol{s}$ conditions T by channel attention and ISP parameter generation via fully connected layers.

4.5 Denoiser Training with Data Augmentation

We synthesize noisy-clean RGB image pairs at low-resolution to train general RGB denoisers. The noisy/clean images are the downscaled raw image ($\boldsymbol{x}^d$) with/without additive noise $\boldsymbol{N}$ transformed to RGB space using T. Formally, the denoiser (D) training minimizes the following objective function,

$$\min_D |T(\boldsymbol{x}^d; \boldsymbol{s}) - D(T(\boldsymbol{x}^d + \boldsymbol{N}; \boldsymbol{s}))|, \tag{7}$$

where $\boldsymbol{s}$ is the style parameter in equation 6. Our denoising framework allows rich augmentation for data synthesis. First, scaling and intensity augmentation (SIA) increases the content diversity by changing the image resolution and pixel values from 0.5× to 1.5×. Second, we randomly scale the noise parameters, β_1 and β_2, from 0.5× to 1.5×. This augmentation alleviates the noise estimation

error in Section 4.3. Lastly, when the multiple noisy images are given, we can augment the noise parameters and the style parameters across different images. Overall, the objective function of our denoiser training equation 7 becomes

$$\min_{D} |T(SIA(\boldsymbol{x}^d); \boldsymbol{s}') - D(T(SIA(\boldsymbol{x}^d + \boldsymbol{N}'); \boldsymbol{s}'))|, \tag{8}$$

where SIA is the scale and intensity augmentation, $\boldsymbol{s}'$ is the augmented style parameter, and $\boldsymbol{N}'$ is the additive noise with augmented noise parameters. At testing, the denoiser takes the RGB noisy image ($\boldsymbol{y}$) as input, just like the conventional CNN-based approaches.

5 Experiments

5.1 Implementation Details

Downscaling We downscale a raw image $\boldsymbol{x}$ to $\boldsymbol{x}^d$ by bicubic interpolation after asymmetric 2D Gaussian blurring with the kernel size of 21×21. We randomly select the standard deviation of the Gaussian blur from $0.25 \times ds$ to $0.75 \times ds$ for each dimension, where ds denotes the downscaling factor randomly selected in the range of $[1.5, 2.5]$. We use the same hyper-parameters for noise estimation, ISP estimation, and denoiser training, unless otherwise specified.

Optimization We use Adam (Kingma & Ba, 2015), 128×128 image patches, and the batch size of 64 for all experiments. Noise estimation adopts $2.5 \times e^4$ iterations with the initial learning rate of $1 \times e^{-4}$ which becomes a tenth part in every $5 \times e^3$ iterations. We use the same initial learning rates for ISP estimation and denoiser training for $5 \times e^5$ iterations without the learning rate decay.

Denoiser We use two simple networks as denoiser to present generalizability of the proposed training scheme. Specifically, NERDS+DnCNN uses DnCNN (Zhang et al., 2017) and NERDS+D uses a ResNet-style architecture, composing a global skip connection and 32 residual blocks. Each block has two convolutional layers and one ReLU activation with 64 filters and 3×3 kernels.

Dataset We use BSD68 (Martin et al., 2001) which consists of 68 gray-scale images to evaluate the performance of noise estimation. For real image denoising, we use raw noisy and RGB noisy images on SIDD (Abdelhamed et al., 2018), DND (Plotz & Roth, 2017), and MIT-Adobe FiveK (Bychkovsky et al., 2011). SIDD (Abdelhamed et al., 2018) consists of training, validation, and benchmark datasets. We use 1,280 256×256 patches from 40 noisy images on the benchmark for denoiser training. In the setting of extra images, we use 50 noisy images on the training dataset with low ISO levels of 100 and downscale the noisy images with the scaling factor from 1.1 to 1.2. For DND (Plotz & Roth, 2017), we use 1,000 512×512 patches from 50 noisy images on the benchmark. We evaluate the denoising performances on the benchmarks by submitting the results to the public websites for SIDD and DND. MIT-Adobe FiveK (Bychkovsky et al., 2011) consists of 5,000 raw images and paired RGB images retouched by 5 photographers. Each RGB image has own RAW2RGB conversion using Adobe Lightroom while the raw image contains real camera noises. We demonstrate an extreme scenario where only 5 noisy images are available for denoiser training.

5.2 Results for Noise Estimation and Synthesis

We first validate our noise estimation on additive Poisson-Gaussian noise to images on BSD68 (Martin et al., 2001), and then visualize the noise synthesis at low-resolution from noisy images on MIT-Adobe FiveK (Bychkovsky et al., 2011).

Poisson-Gaussian noise estimation We demonstrate the effectiveness of our noise estimation on Poisson-Gaussian noises (NERDS-raw) by comparing with Foi *et al.* (Foi et al., 2008), Liu *et al.* (Liu et al., 2014), and PGE-Net (Byun et al., 2021) which enable Poisson-Gaussian noise estimation from noisy images. Table 1 presents the average of the estimated values of (β_1, β_2) in four different noise levels. In most cases, NERDS-raw estimates the most accurate noise parameters.

Noisy-clean RGB image synthesis Figure 5 shows noise synthesis results using NERDS. Each real image from MIT-Adobe FiveK has own RAW2RGB conversion. NERDS-noisy contains realistic noises specialized to each real image, such as blue/dark noises in dark area with none i.i.d

Table 1: The average values of $(\hat{\beta}_1, \hat{\beta}_2)$ estimated from BSD68 with additive Poisson-Gaussian noise level of (β_1, β_2). Bold denotes the best result.

Noise level (β_1, β_2)	Foi *et al.* (Foi et al., 2008) $(\hat{\beta}_1, \hat{\beta}_2)$	Liu *et al.* (Liu et al., 2014) $(\hat{\beta}_1, \hat{\beta}_2)$	PGE-Net (Byun et al., 2021) $(\hat{\beta}_1, \hat{\beta}_2)$	NERDS-raw (Ours) $(\hat{\beta}_1, \hat{\beta}_2)$
(0.100, 0.0200)	(0.096, 0.042)	(0.072, 0.045)	(0.098, 0.0030)	(**0.100**, **0.0229**)
(0.100, 0.0002)	(0.097, 0.035)	(0.071, 0.044)	(0.095, **0.0001**)	(**0.101**, **0.0001**)
(0.050, 0.0200)	(0.049, 0.031)	(0.040, 0.040)	(0.052, 0.0001)	(**0.051**, **0.0245**)
(0.050, 0.0002)	(**0.051**, 0.018)	(0.039, 0.034)	(**0.051**, 0.0001)	(0.052, **0.0002**)

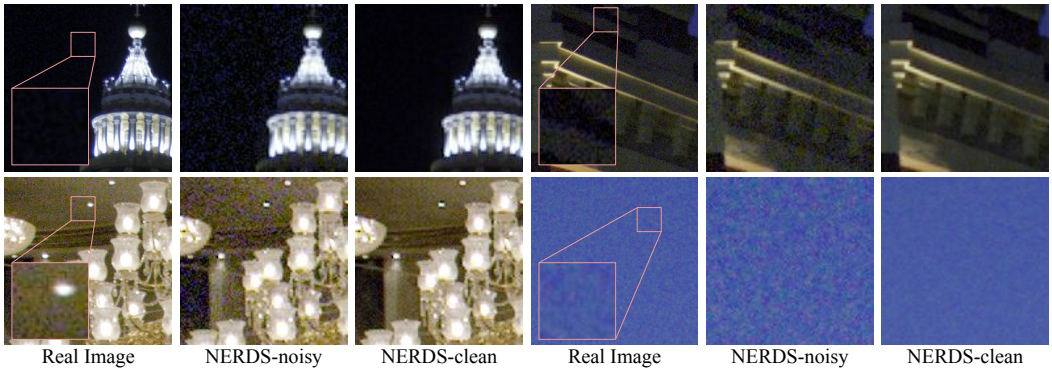

Figure 5: Noise synthesis results using NERDS. NERDS can synthesize noisy-clean RGB image pairs at low-resolution from single noisy images. NERDS-noisy and NERDS-clean denote synthetic RGB images with and without noises. This example uses the downscaling factor of 2. (*Zooming-in for the best view.*)

characteristics. To the best of our knowledge, NERDS is the first work to generate the realistic noisy images and the paired clean images for the unknown RAW2RGB conversions (or ISPs) by using only raw-RGB noisy image pairs. Existing works for noise synthesis (Brooks et al., 2019; Zhang et al., 2022; Zamir et al., 2020; Abdelhamed et al., 2019; Kousha et al., 2022) require real noisy-clean image pairs, metadata, and ISPs. Thus, naìve comparisons betwwen NERDS and the existing methods are unfair, but we present them in the Appendix.

5.3 Comparisons to the SotA Denoising Methods

Results on benchmarks Given that NERDS trains denoisers without clean images, we compare our denoisers with the SotA denoising methods that *do not use the pairs of real noisy-clean images*. Specifically, we compare GAT+BM3D (Dabov et al., 2007), N2V (Krull et al., 2019), AP-BSN (Wooseok Lee, 2022), FBI-D (Byun et al., 2021), C2N+DIDN (Jang et al., 2021), and SCUNet (Zhang et al., 2022) on SIDD and DND benchmarks. Table 2 presents the effectiveness of the proposed denoisers, NERDS+DnCNN and NERDS+D. C2N+DIDN (Jang et al., 2021) synthesizes realistic noises using *unpaired* noisy-clean images, while our NERDS+DnCNN outperforms it with the simpler denoiser (DIDN *vs.* DnCNN). SCUNet (Zhang et al., 2022) synthesizes realistic noises using high-quality clean images and the predetermined noise models including specific noise levels and ISP pipelines. The other works require only noisy images via prior-based filtering (Dabov et al., 2007), self-supervised learning (Krull et al., 2019; Wooseok Lee, 2022; Wu et al., 2020), and noise estimation (Byun et al., 2021). The works without clean images perform denoising in raw image space and received the results in RGB image space by submitting the denoised raw images to the public websites (Abdelhamed et al., 2018; Plotz & Roth, 2017). They often fail to remove noises in RGB image space, given that they assume strong noise characteristics such as Poisson-Gaussian distributions and the i.i.d property that do not hold in the RGB image space. The Appendix provides more qualitative results and the comparisons with the noise synthesis methods which use the pairs of real noisy-clean images.

Ablation Study Our NERDS enables rich and effective augmentation for denoiser training. Table 3 demonstrates the ablation study on the data augmentation. The setting without image scale augmentation (Table 3(1)) uses a fixed downscaling factor of 2. Each component improves the restoration performances. In particular, noise parameter augmentation improves over than 0.6 dB,

Table 2: PSNR (dB)/SSIM on RGB SIDD and DND benchmarks. Bold denotes the best result. ✓denotes accessible types of images at training. Extra images denote that images other than the noisy images of the benchmark are used for training.

Dataset	GAT+BM3D	N2V	AP-BSN	FBI-D	C2N+DIDN	SCUNet	NERDS+DnCNN	NERDS+D	
Clean images	-	-	-	-	✓	✓	-	-	-
Extra images	-	-	-	✓	✓	✓	-	-	✓
Synthetic pairs	-	-	-	-	✓	✓	✓	✓	✓
SIDD	34.61/0.879	32.85/0.847	36.91/0.931	38.07/0.942	35.35/0.937	22.89/0.797	36.42/0.923	37.40/0.941	**38.28/0.949**
DND	37.98/0.920	35.82/0.902	38.09/0.937	38.98/0.945	37.28/0.924	-	38.21/0.941	**39.34/0.950**	-

Table 3: Ablation study on data augmentation for NERDS+D. PSNR (dB)/SSIM on RGB SIDD validation.

Augmentation	(1)	(2)	(3)	(4)	(5)	(6)
Image scale	-	✓	✓	✓	✓	✓
Image intensity	-	-	✓	✓	✓	✓
Noise parameter	-	-	-	✓	✓	✓
Style parameter	-	-	-	-	✓	✓
Extra images	-	-	-	-	-	✓
SIDD	35.63/0.897	36.79/0.928	37.16/0.935	37.84/0.944	38.02/0.946	**38.51/0.950**

Real Image | CycleISP | NERDS+D (Ours) | Real Image | SCUNet | NERDS+D (Ours)

Figure 6: Qualitative comparisons of denoising results on MIT-Adobe FiveK (Bychkovsky et al., 2011). Pink arrows indicate the remaining noise of CycleISP and the oversmooth textures of SCUNet while our denoiser generates crisp images. (*Zooming-in for the best view.*)

given that it can alleviate noise estimation error. The usage of extra images enables high-quality clean image synthesis by downscaling images with low noise levels and small scaling factors.

Results on MIT-Above FiveK We evaluate CycleISP (Zamir et al., 2020), SCUNet (Zhang et al., 2022), and NERDS+D on retouched images from MIT-Adobe FiveK (Bychkovsky et al., 2011). CycleISP (Zamir et al., 2020) employs supervised learning on SIDD training dataset with additional synthetic data using the predetermined noise levels and ISP pipeline. Nevertheless, CycleISP fails to denoise the retouched image as visualized in Figure 6. SCUNet (Zhang et al., 2022) is trained on high-quality images with practically designed additive noise, but SCUNet often oversmooths textures. These results are due to different noise distributions between the training images and the test images. In contrast, NERDS+D removes severe real noise while maintaining image details. We will report more qualitative results in the Appendix.

6 Conclusion

We present a general framework to train denoisers from noisy images, called NERDS. The framework composes noise estimation, ISP estimation, and denoiser training. For noise synthesis, we estimate Poisson-Gaussian noise in raw images and ISP (or RAW2RGB conversion) for each RGB image. NERDS allows rich data augmentation for accurate denoiser training. Experimental results show the state-of-the-art restoration accuracy on real noise benchmarks.

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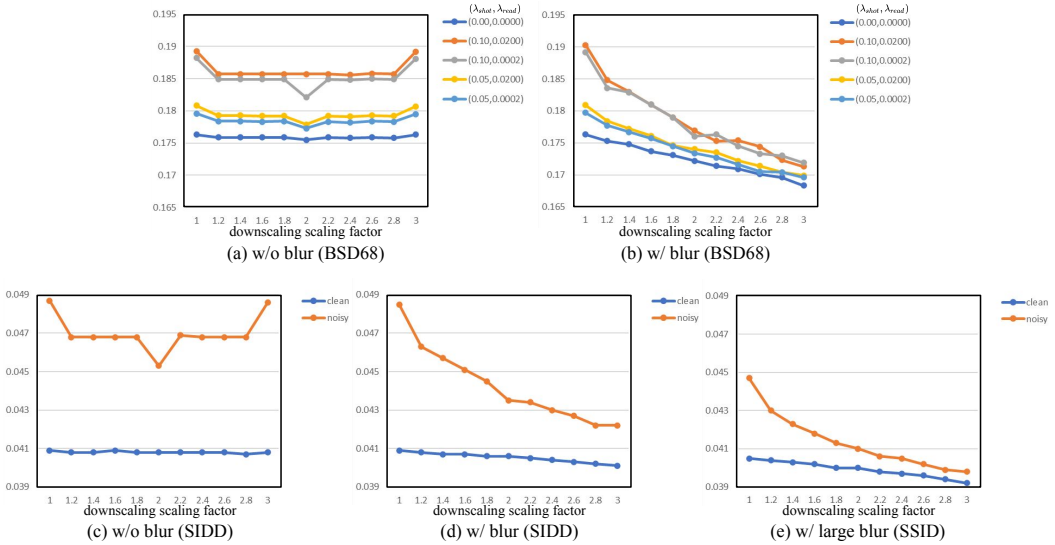
A Appendix

A.1 Discussions

A.1.1 Clean Image via Downscaling

The *optimal* clean image via downscaling is a noise-free low-resolution image that has the same statistics as the true signal (clean high-resolution image). Empirically, we regard the raw images downscaled after burring (low-pass filtering) as raw *pseudo*-clean images. However, blurring images breaks the optimal setting when image structures are too small (*e.g.*, 1-pixel dots) or the noise is too severe compared to the size of the blur. Figure 7 shows the evidence and limitations of the utility of pseudo-clean images used in NERDS. First, the images downscaled without pre-blurring have similar statistics to those of the images before downscaling. This indicates that the image scaling can be regarded as capturing an image at different distances between an object and a camera. Second, the blurring operation reduces the std values of noisy images drastically more than clean images. This is why we use downscaled images as pseudo-clean images. However, blurring also reduces the std values of clean images, making it challenging to find *optimal* pseudo-clean images without clean

data. To alleviate this difficulty, we estimate the noise by gradient-descent-based optimization using ADAM and adopt augmentation of noise parameter scaling ($\times 0.5 \sim \times 1.5$) for accurate denoiser training.



(a) w/o blur (BSD68) (b) w/ blur (BSD68) (c) w/o blur (SIDD) (d) w/ blur (SIDD) (e) w/ large blur (SSID)

Figure 7: Standard deviation (std) of downscaled images. Blue lines denote the std of clean images while the others denote the std of noisy images. Downscaling without pre-blurring maintains the std values through scaling on both BSD68 ((a)) and SIDD ((c)). In contrast, blurring before downscaling reduces the std values of noisy images drastically than clean images ((b) and (d)). (e) Large blur kernels ($2\times$ larger than the kernels used in NERDS) reduce the std values more steeply.

We further analyze the effectiveness of blur kernels by measuring KL divergence between synthesized noisy images and real noisy images. The lower value the better. Table 4 visualizes ablation study on the size of blur kernels on SIDD dataset. While noise estimation w/ clean image perform the upper bound score, noise estimation w/ blur achieves comparable performances to noise estimation w/ clean image. In both cases of w/o blur and w/ large blur, KL divergence scores increase than noise estimation w/ blur. These results indicate that the downscaled images work as clean images well with the proper size of blur kernels.

Table 4: $\mathcal{D}_{KL}$ comparison. Noise estimation w/ blur achieves comparable performances to w/ clean image.

Noise Estimation	w/o blur	w/ blur	w/ large blur	w/ clean image
$\mathcal{D}_{KL}$	0.1710	0.0344	0.0535	**0.0079**

A.1.2 Noise Distribution of Raw Images

Our NERDS assumes that the raw images have the noise that follows Poisson-Gaussian distribution. However, the image sensor of a smartphone or a digital camera is a black box. We do not know what kind of post-processing has been applied to the raw images, or whether the noise level (parameters) in the metadata represent the proper parameters of Poisson-Gaussian distribution. For instance, one of the noise levels in the metadata of Galaxy S6 (β_2 in Figure 8) equals zero for all images, which is theoretically impossible for both shot and read noise parameters of the Poisson-Gaussian model. Nonetheless, Figure 8 presents a similar tendency between the noise levels in the metadata (β_1, β_2) and the estimated noise parameters (λ_{shot}, λ_{read}). Thus, we approximate the noise distribution in raw images as Poisson-Gaussian noise and show that NERDS+D can achieve satisfactory denoising results using the estimated Poisson-Gaussian noise.

A.1.3 Efficient Inference at Test Time

The proposed method consists of four steps; noise estimation in raw images, ISP estimation, denoiser training, and denoiser testing. Each step described above has the latency described in Table 5. With-

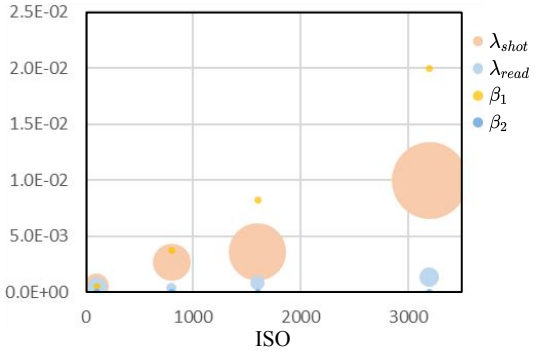


Figure 8: Noise distribution of images from Galaxy S6. β_1 and β_2 are the noise levels of metadata, while λ_{shot} and λ_{read} are the estimated noise parameters for Poisson-Gaussian distribution using NERDS. While (β_1, β_2) have specific values at each ISO level, the radius of the circles for λ_{shot} and λ_{read} represents the standard deviation of the estimated values for each image on SIDD training dataset.

out test-time adaptation, the denoiser (NERDS+D) requires only the testing step. We use GeForce RTX 2080 Ti GPU and an HD image for testing.

Table 5: Latency analysis for test-time adaptation.

	Noise Estimation	ISP Estimation	Denoiser Training	Denoiser Testing
Latency	30 m	1 h	6 h	0.1 s

The noise estimation, ISP estimation, and denoiser training using noisy test images are time-consuming. To skip the processes at test time, Table 6 presents a generalization test for NERDS+D trained on different datasets. NERDS+D trained on DND has accurate restoration performance on DND but performs 2 dB lower PSNR on SIDD than the model trained on SIDD. In contrast, NERDS+D trained on SIDD performs accurate restoration on both datasets. This phenomenon indicates that SIDD contains noise distributions similar to DND and that well-designed noisy images enable generalized denoiser training. For instance, camera manufacturers can collect training datasets of only noisy images concerning the image sensor, ISP, and expected image retouching.

Table 6: Generalization test for NERDS+D on different training datasets without clean data. PSNR (dB)/SSIM on sRGB SIDD validation and DND benchmark. Bold denotes the best result.

	NERDS+D	
Training Data	SIDD	DND
SIDD	38.51/0.950	36.26/0.923
DND	39.14/0.949	39.34/0.950

A.2 Comparisons to Noise Synthesis Methods using Real Noisy/Clean Image Pairs

The recently proposed methods (Abdelhamed et al., 2019; Chang et al., 2020; Zhang et al., 2021; Kousha et al., 2022) synthesise noisy images with novel noise models. These methods use noise/clean image pairs and metadata that are not accessible at test time, such as the DND dataset. Although the proposed method is a general framework for denoising training without a clean image, we present comparisons with these methods by evaluating the noise estimation results with denoising performance and KL divergence.

Denoising performance. Table 7 presents denoising performances for raw images on the SIDD benchmark, where we use DnCNN as the denoiser. Although NERDS does not use clean images for noise estimation, noise synthesis, and denoiser training, NERDS achieves the best PSNR score.

Table 8 presents denoising performances for RGB images on the SIDD benchmark, where all methods use DnCNN as the denoiser. NERDS achieves the best PSNR/SSIM scores. When converting

the denoised raw images using NERDS to RGB images, the PSNR is 35.74 dB which is lower than RGB image denoising (36.42 dB).

Table 7: RAW image denoising on the SIDD benchmark. NERDS achieves the best PSNR score. We use DnCNN as the denoiser for NERDS.

	Gaussian	Noise Flow (Abdelhamed et al., 2019)	Camera-Aware (Chang et al., 2020)	NERDS (Ours)
PSNR (dB)/SSIM	43.63/0.968	48.52/0.992	48.71/**0.993**	**48.93**/0.985

Table 8: RGB image denoising on the SIDD benchmark. NERDS achieves the best PSNR/SSIM scores. All methods use DnCNN as the denoiser.

	Gaussian	Noise Flow	C2N	sRGB Noise Flow (Kousha et al., 2022)	NERDS (Ours)
PSNR (dB)/SSIM	32.72/0.873	33.81/0.894	33.76/0.901	34.74/0.912	**36.42/0.923**

KL divergence. Table 9 presents the comparisons of KL divergence ($\mathcal{D}_{KL}$) between synthesized noisy images and real noisy images. The lower values the better. The proposed method outperforms all compared methods when using the clean images. We could not reproduce the results of sRGB Noise Flow (Kousha et al., 2022) since the source code was not available. The score reported in the paper is 0.044 for sRGB Noise Flow, where Noise Flow scores 0.198. The scores of KL divergence are dependent on hyperparameters.

Table 9: $\mathcal{D}_{KL}$ comparison. The proposed method with clean data outperforms all compared methods.

	Calibrated P-G	Noise Flow	Camera-Aware	NERDS w/ clean data (Ours)	NERDS (Ours)
Clean data	✓	✓	✓	✓	
$\mathcal{D}_{KL}$	1.5147	0.0481	0.0144	**0.0079**	0.0344

B Qualitative Results

B.1 Synthesized Noisy-Clean Image Pairs

Figure 9 visualizes noise synthesis results using NERDS. NERDS-clean contain low-level noise while NERDS-noisy present severe noise similar to the real noisy images. We have empirically found that denoisers *do not* learn to remove noises in NERDS-clean. This phenomenon is because the blurring and downscaling process in NERDS distorts the noise of raw images while denoisers learn to remove Poisson-Gaussian noise in the raw images. Moreover, given that NERDS does not require any clean data, NERDS successfully synthesizes noisy-clean image pairs on DND and MIT-Adobe FiveK datasets which are not available to access clean images.

B.2 Denoised Images

We presents more images denoised by NERDS+D on SIDD (Figure 10), DND (Figure 11), and MIT-Adove FiveK (Figure 12). While AP-BSN (Wooseok Lee, 2022), FBI-D (Byun et al., 2021), SCUNet (Zhang et al., 2022), C2N (Jang et al., 2021)+DIDN (Yu et al., 2019), and CycleISP (Zamir et al., 2020) often fail to restore image patterns in GT, NERDS+D successfully recover the original structures. AP-BSN uses pixel shuffle for self-supervised learning to decorrelate spatially but also loses spatial information for denoising. FBI-D learns raw image denoising for Poisson-Gaussian noise, but denoising raw images is an indirect approach for the human visual system (or RGB space). SCUNet over-smooth or over-sharpen images. This restoration style helps to generate readable characters, but it can distort the patterns in GT (See Figure 10). C2N+DIDN is the denoiser trained by generating noisy images from clean images using both noisy and clean images on SIDD datasets. For DND benchmarks, C2N+DIDN sometimes generates artifact or noise that significantly drops the restoration accuracy (See Figure 11). In contrast, NERDS+D uses only noisy images on DND benchmarks to generate noisy-clean image pairs for accurate denoiser training. CycleISP is the denoiser trained by paired noisy-clean images on SIDD datasets and paired images synthesized by the metadata of DND benchmarks. CycleISP performs the highest PSNR and SSIM on both SIDD and DND benchmarks compared to the methods in Table 2. However, CycleISP fails to remove the noises on MIT-Adobe FiveK (See Figure 12). This failure comes from the noise distribution of RGB images mismatched between MIT-Adobe FiveK and SIDD (or DND) datasets.

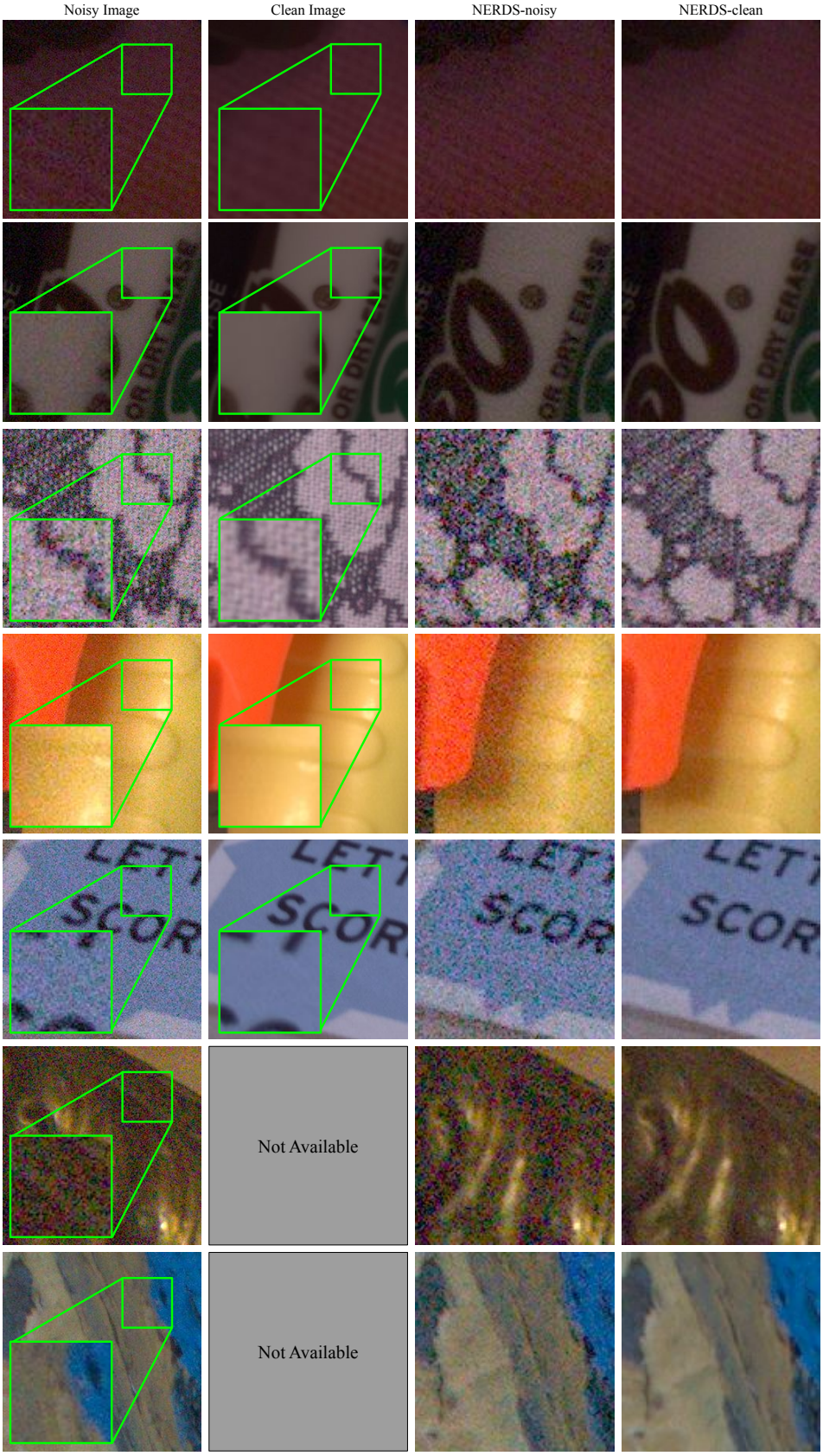


Figure 9: Examples of noisy synthesis results using NERDS. We upscale NERDS-noisy, NERDS-clean, and the green boxes with the scaling factor of 2 for visualization.

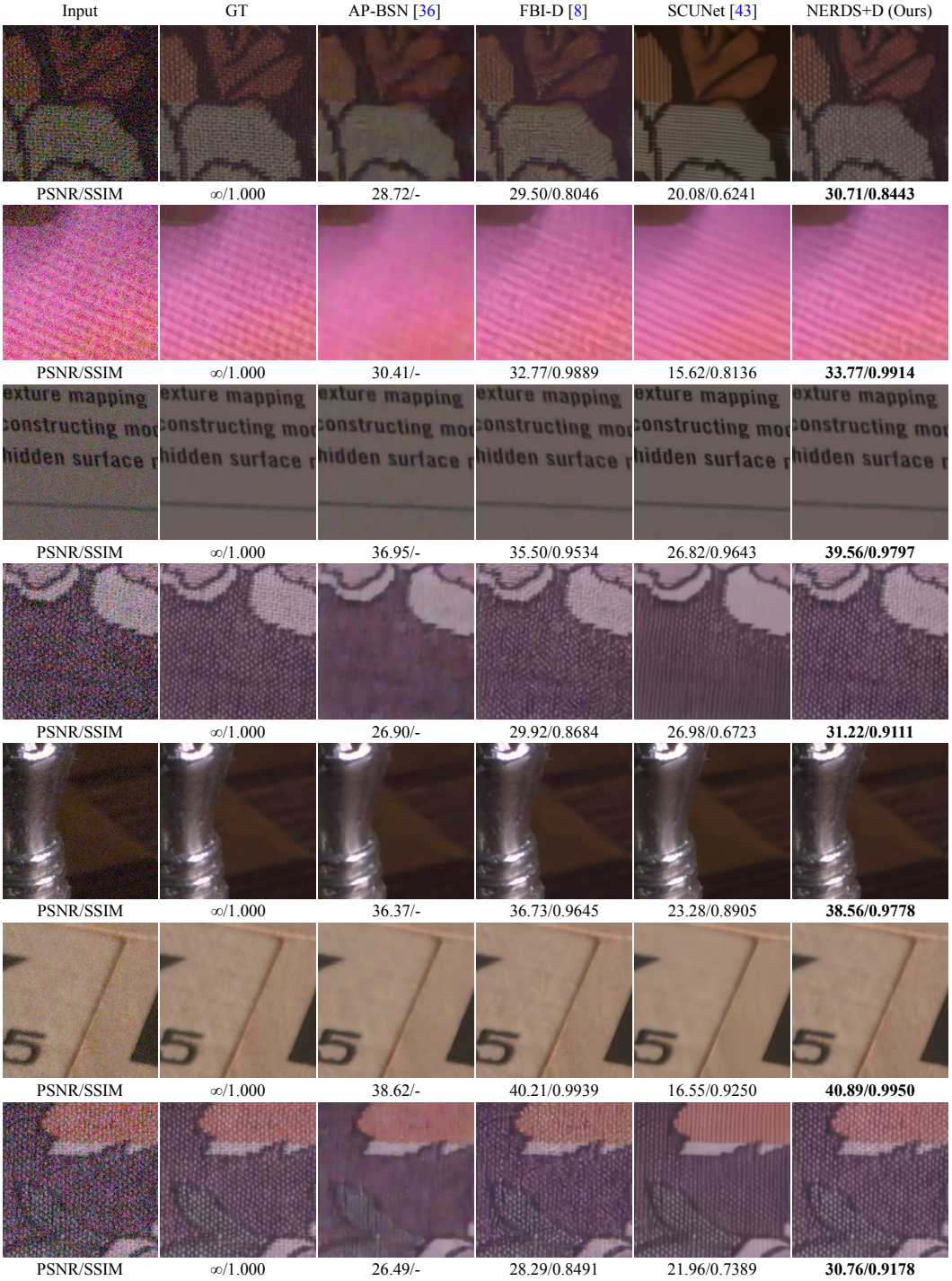


Figure 10: Qualitative results on SIDD validation.

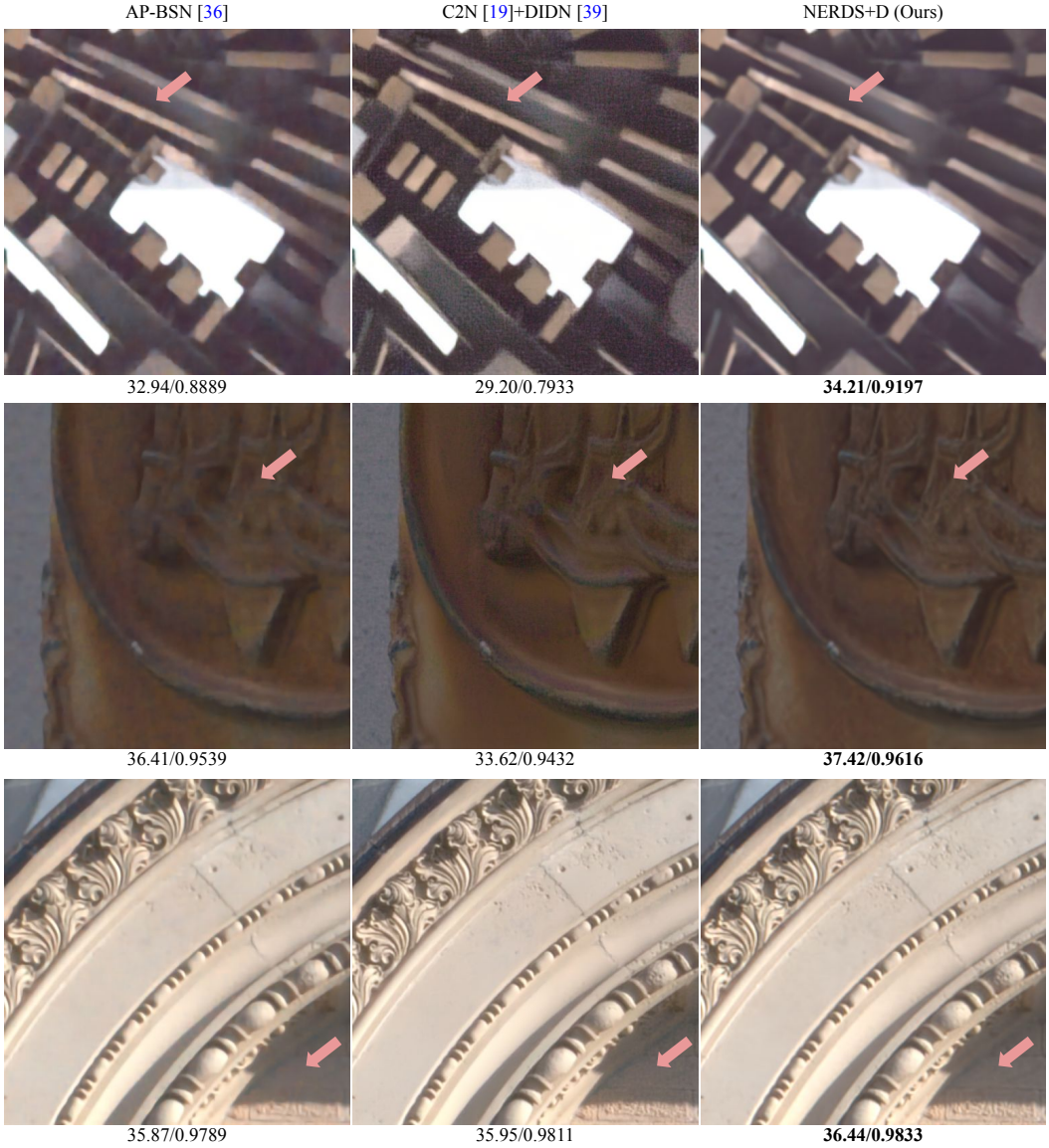


Figure 11: Qualitative results and PSNR (dB)/SSIM on DND.

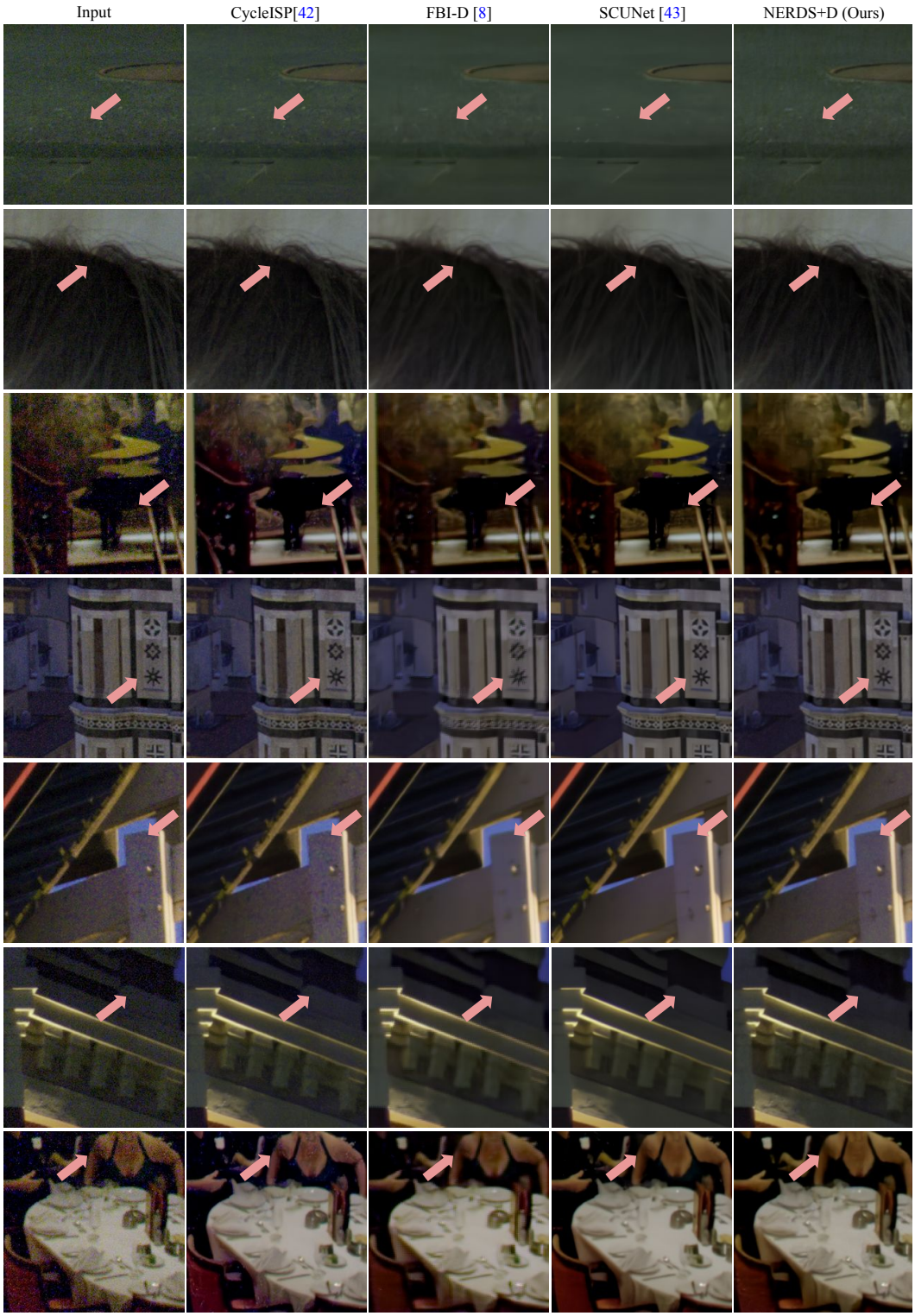


Figure 12: Qualitative results on MIT-Adobe FiveK. CycleISP often fails to remove noise, while FBI-D and SCUNet over-smooth or over-sharpen images. Note that NERDS+D uses only 5 test noisy images and estimated noise parameters from them for training. (*Zooming-in for the best view.*) We use T of NERDS to convert RAW images denoised by FBI-D to RGB images.