# Noise2NoiseFlow: Realistic Camera Noise Modeling without Clean Images —Supplemental Material—

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### 1. Training details

In this section, we give more details about the training procedure. As mentioned in the main paper, we used Adam [3] as optimizer in all of our experiments. We pre-trained the denoiser with N2N loss (Eq. 5 of the main paper) for 2,000 epochs. Also note that the denoiser pre-training step was used only to boost training under different setups, and is not a vital part of the overall training. Training the original Noise2NoiseFlow model from scratch will also produce almost the same results (*NLL*: -3.498,  $D_{KL}$ : 0.0275, PSNR: 52.65).

The supervised DnCNN was trained with MSE using the clean/noisy pairs from SIDD-Medium. Both denoiser pretraining and supervised training used an initial learning rate of  $10^{-3}$ , which was decayed to  $10^{-4}$  at epoch 30, and  $5 \times 10^{-5}$  at epoch 60. We used orthogonal weight initialization [2] for the denoiser architectures and the exact same initial weights for the noise model as used in the Noise Flow paper.

The denoiser was a 9 layer DnCNN and was the same in all experiments except where noted. Noise Flow was reimplemented in PyTorch [4] and carefully tested for consistency against the original implementation. Joint training used a constant learning rate of  $10^{-4}$  for 2,000 epochs though no improvements were generally observed after ~ 600 epochs.

#### 2. Synthetic Noise Experiment

In order to demonstrate that our framework can retrieve the parameters of a supervised trained noise model, we have conducted a synthetic noise experiment. In this setting, we first trained a heteroscedastic Gaussian noise model, which was implemented as a flow layer in Noise Flow. For simplicity, we only took one camera and one ISO setting—namely, iPhone 7 and 800 as ISO level as we had adequate image data for training and evaluation. Under the mentioned setting, the model only has two trainable parameters—namely,  $\beta_1$  and  $\beta_2$ . We then use this trained



Figure 1. Convergence curve of the two parameters ( $\beta_1$  and  $\beta_2$  of the NLF model for a specific camera sensor and ISO level. *NF Parameter* corresponds to the parameters learned by a supervised Noise Flow model and *Reconstruction* Corresponds to the NLF parameters learned by a Noise2NoiseFlow model from synthetic data generated by the supervised Noise Flow model. As evidenced by the figures, the model can successfully retrieve the parameters.

model to synthesize noisy image pairs for training a subsequent Noise2NoiseFlow model from scratch with only a heteroscedastic Gaussian layer as its noise model and DnCNN as its denoiser. The results shown in Figure 1 shows that our model can successfully retrieve the parameters of a trained NLF model.

#### **3. Failure Cases**

Although no significant unrealistic behaviour was noticed, we visualize 5 noise samples with the worst  $D_{KL}$  for Noise2NoiseFlow in Figure 2. While the noise samples are not in the best alignment with the real samples, the generated noise patches do not look very unnatural.

## References

- A. Abdelhamed, M. A. Brubaker, and M. S. Brown, "Noise flow: Noise modeling with conditional normalizing flows," in *ICCV*, 2019. 2
- [2] W. Hu, L. Xiao, and J. Pennington, "Provable benefit of orthogonal initialization in optimizing deep linear networks," *arXiv preprint arXiv:2001.05992*, 2020. 1

<sup>\*</sup>Work performed while interns at the Samsung AI Center-Toronto.

(a) Gaussian	(b) Camera NLF	(c) Calibrated P-G	(d) Noise Flow	(e) N2NF	(f) Real Noise	(g) Clean Image
KLD=0.7567	KLD=0.6933	KLD=0.6438	KLD=0.5750	KLD=0.6726		
KLD=0.6175	KLD=0.4291	KLD=0.3624	KLD=0.3266	KLD=0.3933		
KLD=0.5575	KLD=0.3927	KLD=0.3437	KLD=0.2970	KLD=0.3596		
KLD=0.3195	KLD=0.1858	KLD=0.1617	KLD=0,1358	KLD=0.1574		
KLD=0.1158	KLD=0.0192	KLD=0.0561	KLD=0.0738	KLD=0.1274		

Figure 2. Noise synthesis samples from (a) the AWGN model, (b) Camera NLF, (c) Calibrated P-G [5], (d) Noise Flow [1], and our proposed method, Noise2NoiseFlow, compared to the (f) real noise in SIDD for patches where Noise2NoiseFlow has the worst  $D_{KL}$  numbers.

- [3] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *ICLR*, 2015. 1
- [4] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga *et al.*, "Pytorch: An imperative style, high-performance deep learning library," *Advances in neural information processing systems*, vol. 32, 2019. 1
- [5] Y. Zhang, H. Qin, X. Wang, and H. Li, "Rethinking noise synthesis and modeling in raw denoising," in *ICCV*, 2021. 2