Deep Image Prior for Single-Shot, Blind Denoising and Deconvolution

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1 Objective

Goal: Explore non-supervised methods for solving inverse problems, specifically blind denoising and deblurring, where we do not have prior data. We formulate the problem as:

$$y = Ax + \eta$$

where y is the observations, A is the degradation operator and η is additive Gaussian white noise. For denoising: $A = I$. For deblurring, A is the Toeplitz matrix corresponding to the blur kernel.

Motivation: While supervised methods explored in class perform well on these tasks, they **(1)** require large amounts of labelled data and **(2)** can struggle to handle complex noise patterns.

2 Prior Work

2017 Ulyanov et al. [1] introduce the deep image prior – a method for using the parametrized structure of a neural network as a natural image prior..

2020 Ren et al. [2] discuss methods for adapting the deep image prior for the deconvolution/deblurring inverse problem.

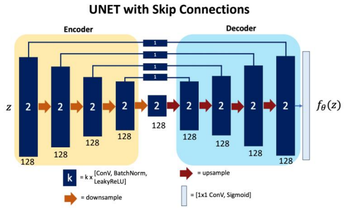
2024 We adapt these methods and benchmark them against supervised algorithms (an upper bound on performance) and other deterministic algorithms. We also explore how adding TV regularization, simpler architectures, and varying levels of noise/blur affects performance.

DIP output, i = 1

3 Architectures

Diagram inspired by [3]

UNET with Skip Connections

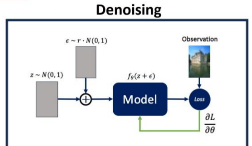


Model$_1$: We adapt the UNET with skip connections network proposed by [1]. The model has 2217831 parameters.

Model$_2$: We implement a simple 2-layer perceptron with Sigmoid activation function for the kernel generator, following advice of [2].

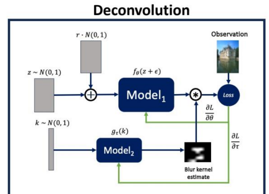
4 Methods

Denoising



Goal: $\min_\theta MSE(f_\theta(z), y)$

Deconvolution



Goal: $\min_{\theta,\tau} MSE(f_\theta(z) * g_\tau(k), y)$

At convergence:

$$\approx f_\theta(z;\ \tilde{\theta})$$

Used Adam optimizer (optimize *f* and *g* simultaneously in deconvolution).

For TV regularization prior: $\min_\theta MSE(f_\theta(z)), y) + \lambda \|f_\theta(z)\|_{TV}$ where λ is a learned hyperparameter.

5 Results

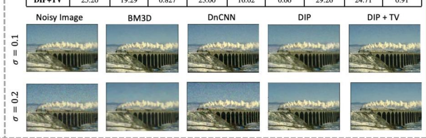
Ground Truth Image (from BSDS300)

Blur Kernel from MNIST (used in deconvolution)

Denoising

Table 1: Denoising Results

Method	$\sigma = 0.1$			$\sigma = 0.2$			Speckle ($\sigma = 0.1$)		
	PSNR$_{gt}$	PSNR$_y$	SSIM$_{gt}$	PSNR$_{gt}$	PSNR$_y$	SSIM$_{gt}$	PSNR$_{gt}$	PSNR$_y$	SSIM$_{gt}$
BM3D	27.24	20.65	0.876	23.59	14.57	0.74	27.38	24.00	0.87
DnCNN	27.13	21.23	0.856	24.07	15.33	0.71	27.94	24.32	0.89
DIP	26.39	20.66	0.829	22.87	16.07	0.66	28.48	24.36	0.90
DIP+TV	25.20	19.29	0.827	23.00	16.02	0.66	29.26	24.71	0.91



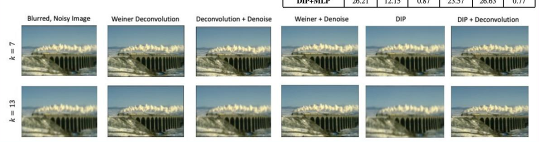
Deconvolution

We perform these experiments using two kernel sizes, $k = 7$ and $k = 13$. We fix the AGWN at $\sigma = 0.01$.

Note that the DIP model does not perform well in the deconvolution task. Priors for the kernel are needed.

Table 2: Deconvolution Results

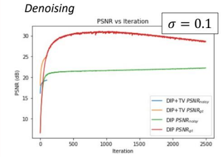
Method	$k = 7$			$k = 13$		
	PSNR$_{gt}$	PSNR$_y$	SSIM$_{gt}$	PSNR$_{gt}$	PSNR$_y$	SSIM$_{gt}$
Weiner	25.28	25.64	0.78	18.3	23.65	0.39
DnCNN	26.25	27.77	0.83	26.02	27.11	0.73
Weiner+DnCNN	33.39	23.51	0.94	32.06	28.42	0.92
DIP	22.09	36.16	0.71	20.32	39.49	0.58
DIP+MLP	26.21	12.15	0.87	23.57	26.63	0.77



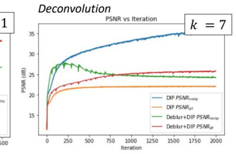
6 Evaluation and Analysis

PSNR

Denoising

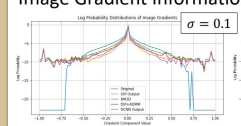


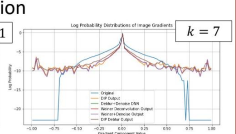
Deconvolution



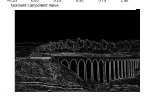
- **[Denoising]:** PSNR ground truth converges. ADMM-DIP could be run for more iters.
- **[Deconvolution]:** Significant overfitting present for DIP model. PSNR$_{noisy}$ continues to increase with more iterations.
- **[Deconvolution]:** DIP+Deblur PSNR$_{noisy}$ plateaus indicating convergence

Image Gradient Information





- Log probability distribution provides insights into closeness to natural images which have sparse gradients [4].
- Most models have roughly the same log intensity while qualitative output varies considerably
- Compute DSSIM for sharpness metric, using Sobel filters to capture edges, shown right (*plots included in report*).



7 Discussion

Key Takeaways:

- DIP is capable of blind denoising and deconvolution for varying noise and blur conditions, though results are usually worse than supervised baselines.
- Regularization noise needed to prevent extreme overfitting.
- Adding TV regularization to DIP usually improves performance.
- In the future, we seek to explore using DIP for single-shot HDR image formation, and low-light deblurring and denoising.

References

[1] Dmitry Ulyanov, Andrea Vedaldi, and Victor S. Lempitsky. Deep image prior. CoRR, abs/1711.10925, 2017

[2] Dongwei Ren, Kai Zhang, Qilong Wang, Qinghua Hu, and Wangmeng Zuo. Neural blind deconvolution using deep priors, 2020

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[4] Yair Weiss and William T. Freeman. What makes a good model of natural images? In *2007 IEEE Conference on Computer Vision and Pattern Recognition*, pages 1–8, 2007