Blind Image Deconvolution based on Deep Image Prior

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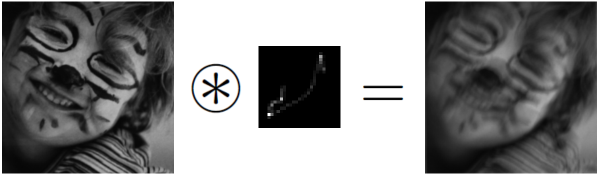
Outline

- Blind image deconvolution
- Deep image prior
- SelfDeblur - DIP in BID
- Stochasticity
- Variational deep image prior

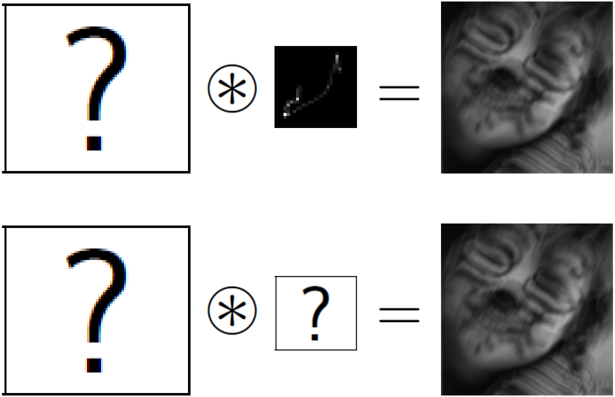
Blurred image model

Blurred image is convolution of sharp image and point spread function (PSF) (assuming space-invariant PSF)

$$\boldsymbol{D} = \boldsymbol{X} \circledast \boldsymbol{K} + \boldsymbol{n}$$

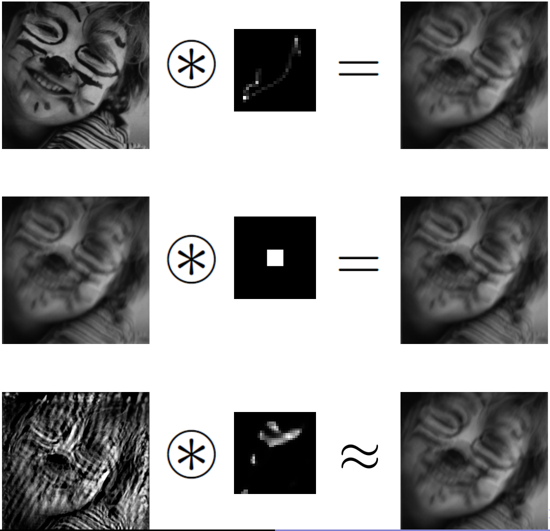


Blind image deconvolution



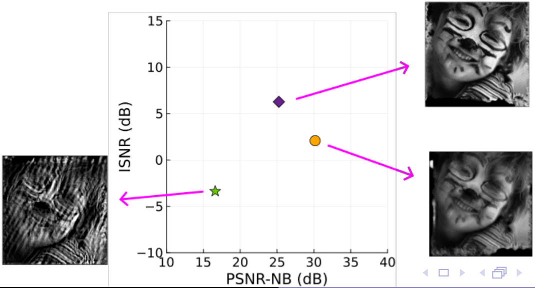
Minimize $\|\boldsymbol{D} - \boldsymbol{K} \circledast \boldsymbol{X}\|$

Blind image deconvolution is highly ill-posed

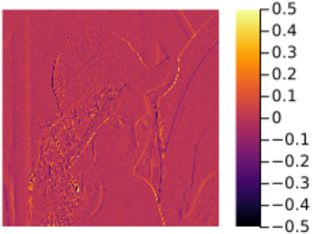


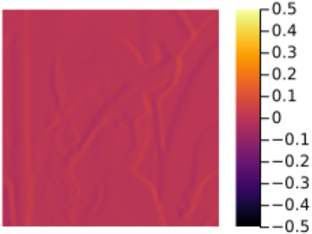
How to measure the quality of a reconstruction

$$
\begin{aligned}
\mathrm{PSNR}(\boldsymbol{x}, \boldsymbol{y}) &= 10 \log_{10}\left(\max_x^2 / \mathrm{MSE}(x, y)\right), \\
\text{PSNR-GT}(\boldsymbol{x}) &:= \mathrm{PSNR}(\boldsymbol{x}, \boldsymbol{x}_{GT}), \\
\text{PSNR-NB}(\boldsymbol{x}) &:= \mathrm{PSNR}(\boldsymbol{x}, \boldsymbol{x}_{NB}), \\
\mathrm{ISNR}(\boldsymbol{x}) &:= \text{PSNR-GT}(\boldsymbol{x}) - \text{PSNR-GT}(\boldsymbol{x}_{NB})
\end{aligned}
$$



Priors for BID

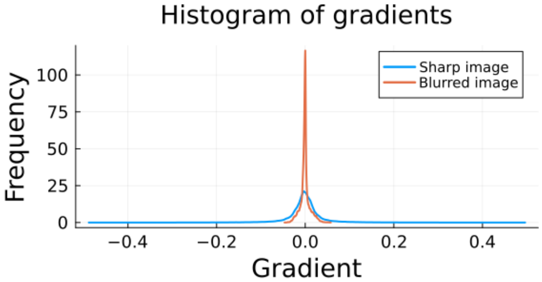




Priors for BID

Methods that use prior

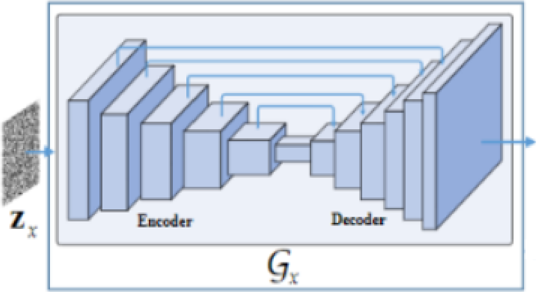
- MAP approach
- Variational Bayes



Algorithms based on Deep Image Prior outperform bayesian methods...

Deep Image Prior[1]

- **Structure of a neural network is a "prior" for the clean image.**
- Operates without any training dataset!
- Denoising, superresolution, inpainting.
- Variants of U-net - convolutional network.



[1] D. Ulyanov, A. Vedaldi, and V. Lempitski. Deep image prior, CVPR, 2018.

DIP prefers smooth images

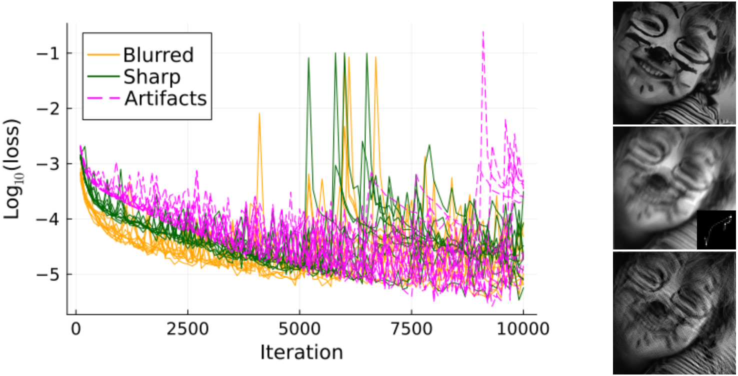
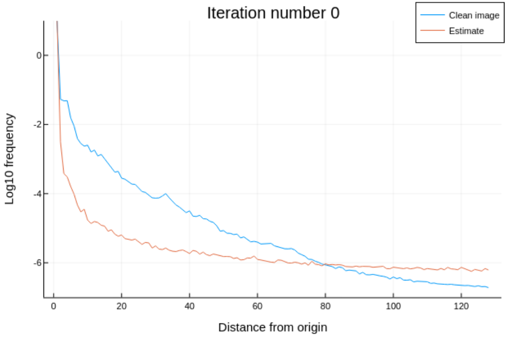


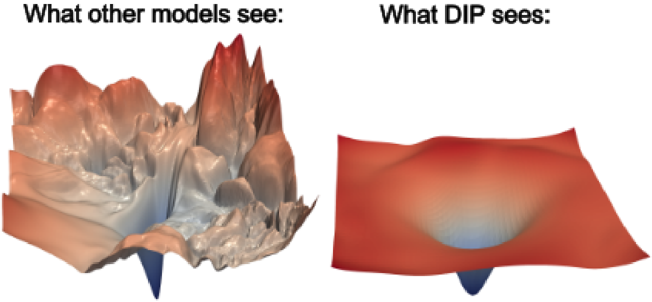
Figure: Comparison of the speed of learning of a sharp image, a blurred image, and an image with artifacts displayed on the right side of the figure.

Low frequencies are learned faster

Frequency in an image = speed of change in pixel intensities $\rightarrow$ details are high frequency information

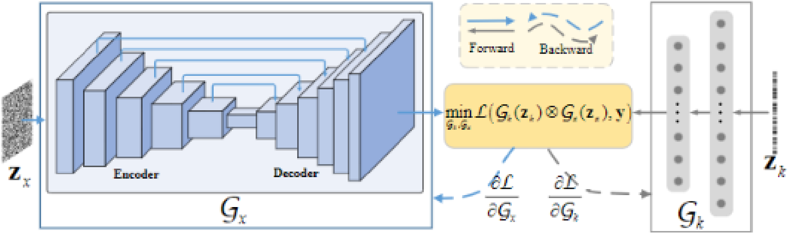


DIP rather chooses a good path towards the solution



H. Li et al.. Visualizing the Loss Landscape of Neural Nets. NeurIPS, 2018.

SelfDeblur[2] - DIP for blind image deconvolution



[2] D. Ren and et al., Neural blind deconvolution using deep priors, CVPR, 2020.

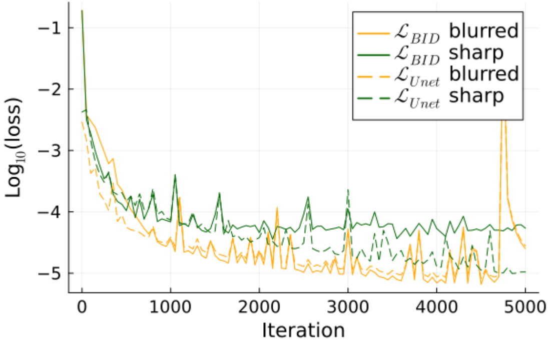
Why should DIP be useful for blind image deconvolution?

Good starting point

PSF initialized as a constant array

$$\mathcal{L}\left(\boldsymbol{\theta}_k, \boldsymbol{\theta}_x \middle| \boldsymbol{x}\right) = \alpha \mathcal{L}_{BID}\left(\boldsymbol{\theta}_k, \boldsymbol{\theta}_x\right) + (1-\alpha)\mathcal{L}_{Unet}\left(\boldsymbol{\theta}_x \middle| \boldsymbol{x}\right),$$

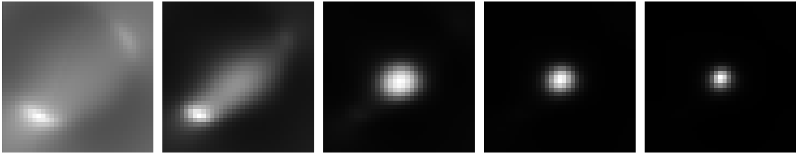
$\alpha = 0.1$:



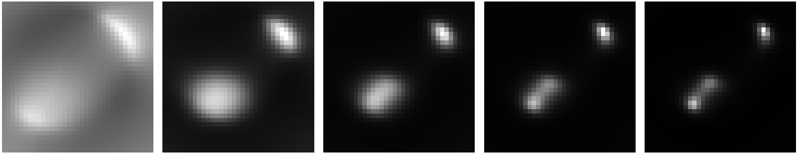
Good starting point

Initialization of PSF - 500 iterations with $\alpha = 0.9$

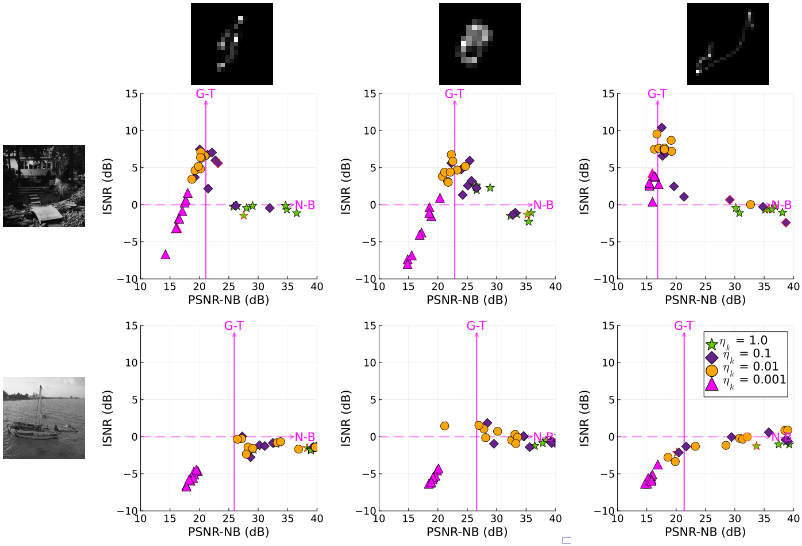
No-blur target:



Ground-truth target:



Choice of the right path - learning rate of the PSF



Choice of the right path - optimiser setting

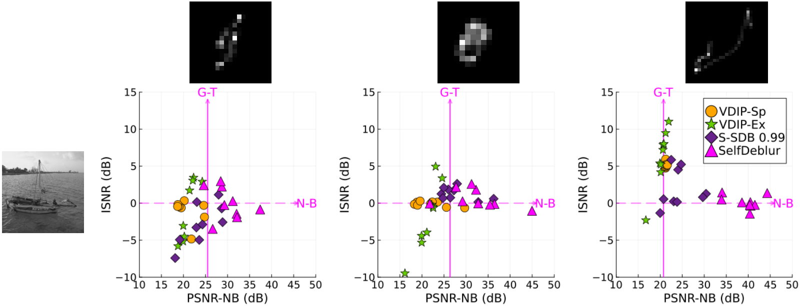


Figure: Deblurring of the problematic image from the Kodak dataset. The sharp image is displayed on the left and the PSFs used for blurring are above the resulting scatterplots. VDIP-Ex denotes VDIP-Extreme, VDIP-SP VDIP-Sparse, and S-SDB 0.99 SimplerSDB with $\beta_1^x = 0.99$.

Choice of the right path - optimiser setting

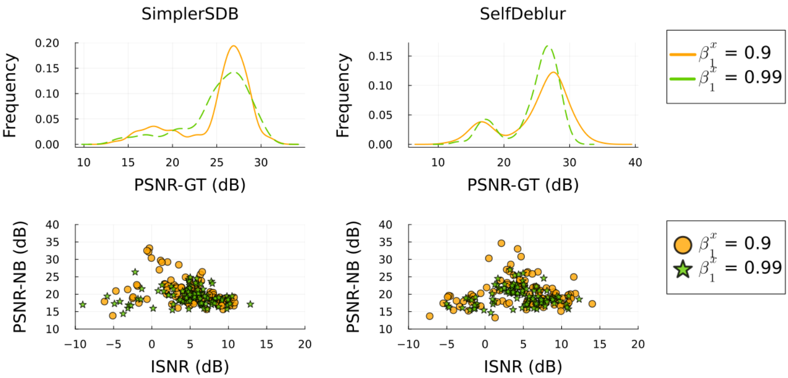
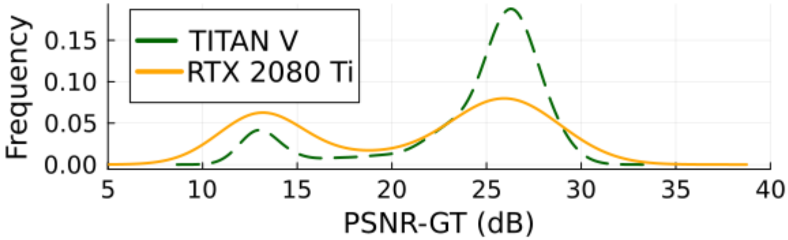


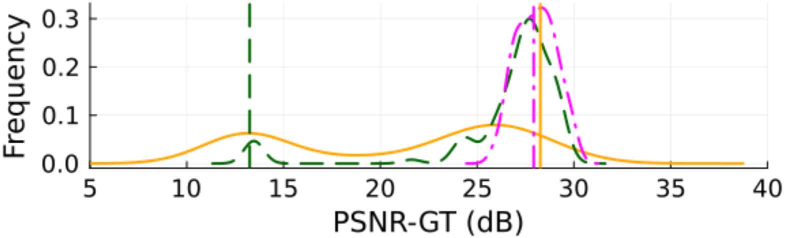
Figure: Sensitivity of the solution to the optimizer hyper-parameters β_1^x in terms of PSNR-NB and ISNR for three runs on the Levin dataset.

DIP does not act as a prior distribution, the combination of DIP and optimization simply finds a good path towards the solution.

Stochasticity - GPU



Stochasticity - Initialization



How to regularize it better?

Bayesian regularization of SelfDeblur

- SelfDeblur can be interpreted as the MAP approach with uniform priors for both the sharp image and the PSF
- SelfDeblur is sensitive to hyperparameters
- Adding TV-regularization of the U-net output to the loss function has been somewhat unsuccessful

Variational DIP

Combination of DIP and traditional sharp image prior[3] in variational Bayes

- Sparse prior
- Extreme-channel prior
- DIP used for the sharp image
- Optimization of ELBO

[3] Huo, D., Masoumzadeh, A., Kushol, R., and Yang, Y.-H. (2023). Blind image deconvolution using variational deep image prior.

Comparison of the algorithms

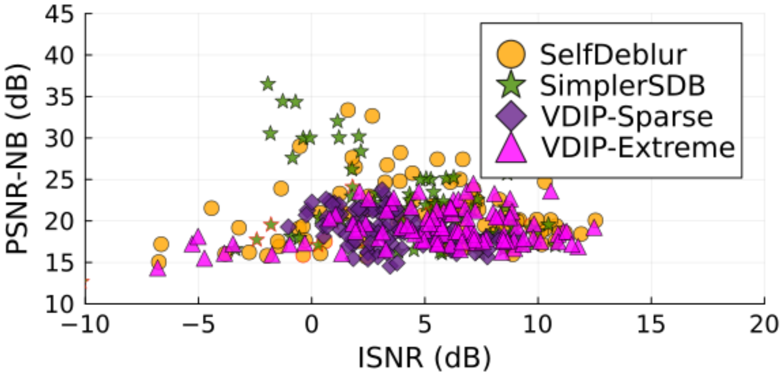


Figure: Three runs on the Levin dataset performed by SelfDeblur, SimplerSDB, VDIP-Sparse, and VDIP-Extreme.

VDIP is more stable

Pretraining

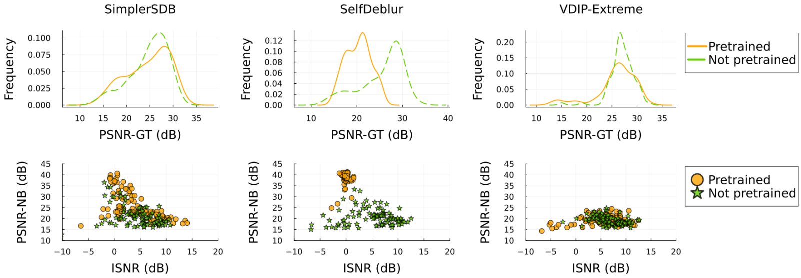


Figure: Effect of pretraining on three runs on the Levin dataset.

VDIP is more stable

SSIM loss

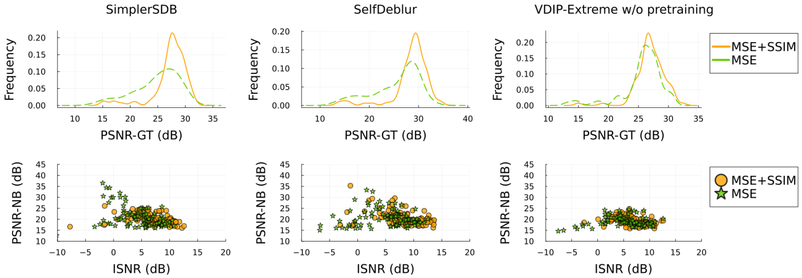


Figure: Effect of switching from MSE loss to SSIM loss after 2000 iterations and pretraining on three runs on the Levin dataset.

Conclusion

DIP is not a prior for the sharp image in BID - combination of DIP and optimization finds a good path towards the solution and does not get stuck in an unpleasant minima.

Even though deep neural networks improve the reconstruction they need to be regularized as well $\rightarrow$ we are going back to the traditional methods