Image Deconvolution with Deep Image and Kernel Priors

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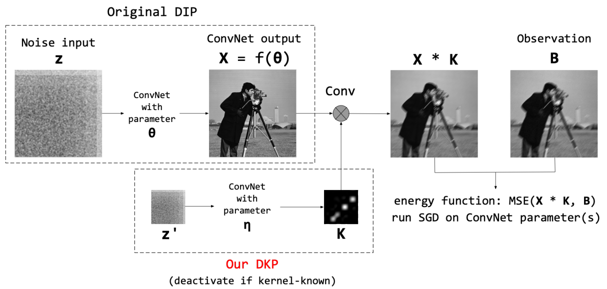
IEEE 2019 International Conference on Computer Vision Workshops
Real-World Recognition from Low-Quality Images and Videos (RLQ)

Abstract: We build an image deconvolution approach with deep image and kernel priors (DIKP) on the success of the recently proposed deep image prior (DIP). We apply deep priors to modelling not only images but also degradation kernels. We show that DIKP improve the performance of learning-free image deconvolution based on the standard benchmark of six standard test images in terms of PSNR and visual effects.

The Convolutional Degradation Model

- Model: $\mathbf{B} = \mathbf{X} * \mathbf{K} + \mathbf{E}$, where $\mathbf{B}$ – observed image, $\mathbf{X}$ – original image, $\mathbf{K}$ – kernel, $\mathbf{E}$ – additive noise.
- Task: Recovering $\mathbf{X}$ from $\mathbf{B}$ **without** training data.
- Settings: Kernel $\mathbf{K}$ known/unknown.
- Baselines: TV/L^1-norm as image/kernel prior resp.

Image Deconvolution with DIKP



- ConvNet hyperparameters act as image/kernel priors.
- ConvNet parameters store image/kernel contents.
- Deep prior structure: *hourglass* with skip connections.
- Noise matrices as network inputs for robustness.

motion blurred | baseline (kernel-known) | ours (kernel-known) | baseline (blind) | ours (blind)

DIKP recover motion blurred cameraman much better than the baselines in both settings.

Gaussian | baseline (k-k) | ours (k-k)

DIKP outperform the baselines in **detail recovery**.

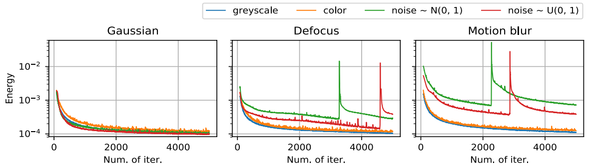
Numerical Performance

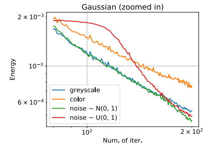
Achieve higher average PSNR values than baselines in both settings (about $\mathbf{1.5}$ **higher** in kernel-known setting and about $\mathbf{5}$ **higher** in blind setting than baselines).

Contributions

- We show that deep priors perform well in image deconvolution, where ConvNets can be utilized as a source of prior knowledge **not only** for natural images but also for **degradation kernels**.
- DIKP result in a significant improvement over traditional regularizers as priors in **learning-free** image deconvolution.

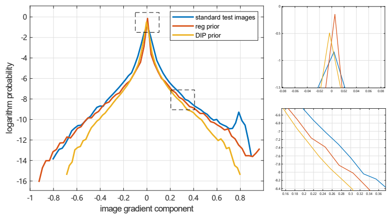
Prior Validation





Noise images are blocked by deep priors while optimizing the energy functions in kernel-known image deconvolution.

Compared with TV-norm regularizer, images recovered by deep prior show a greater similarity to standard test images in terms of gradient distribution.



Numerical Results

KL Divergence $D_{\mathrm{KL}}\left(\widehat{\Pr}_{\mathrm{dikp}} \| \widehat{\Pr}_{\mathrm{std}}\right) = 0.954.$

KL Divergence $D_{\mathrm{KL}}\left(\widehat{\Pr}_{\mathrm{reg}} \| \widehat{\Pr}_{\mathrm{std}}\right) = 1.260.$

Standard Test Images

Six standard test images experimented in our work:

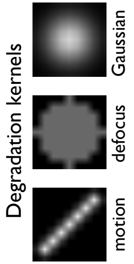
cameraman | house | Lena | boat

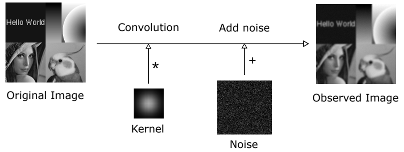
house.c | peppers

containing four greyscale and two color images, with original resolutions either 256×256 or 512×512.

These are classic images that have been used for years in signal processing, which can be accessed from many sources, e.g. *Fabien a. p. petitcolas*, *The USC-SIPI Image Database*, etc.

Artificial Degradation





For each observation, we first convolve the original image by a given kernel, then add a noise term to the convolved image.

This poster is made based on the template by Zoya: http://web.mit.edu/zoya/www/docs.html.
Special thanks to Xiangyu Yue who presents this poster on behalf of the original authors. We also thank Yuqian Zhou and Yingshui Tan for their help with this presentation.