Learning Deep CNN Denoiser Prior for Image Restoration

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IEEE 2017 Conference on Computer Vision and Pattern Recognition

CVPR July 21-26 HONOLULU 2017

Motivation

Existing image restoration methods

- **Model-based optimization methods**
  - Flexible but time-consuming and less effective
- **Discriminative learning methods**
  - Fast and effective but application-specific

Basic idea

- With the aid of variable splitting techniques such as alternating direction method of multipliers (ADMM) and half quadratic splitting (HQS) algorithms, denoiser prior can be plugged in as a modular part of model-based optimization methods to solve other inverse problems.
- Learning fast and expressive discriminative CNN (convolutional neural network) denoisers.

Half Quadratic Splitting (HQS) Algorithm

The general model for image restoration

$$min_{\boldsymbol{x}} \ \|\boldsymbol{y}-\boldsymbol{H}\boldsymbol{x}\|_2^2+\lambda\cdot R(\boldsymbol{x})$$

Introducing an auxiliary variable $\boldsymbol{z}$ ($\boldsymbol{z}\approx\boldsymbol{x}$)

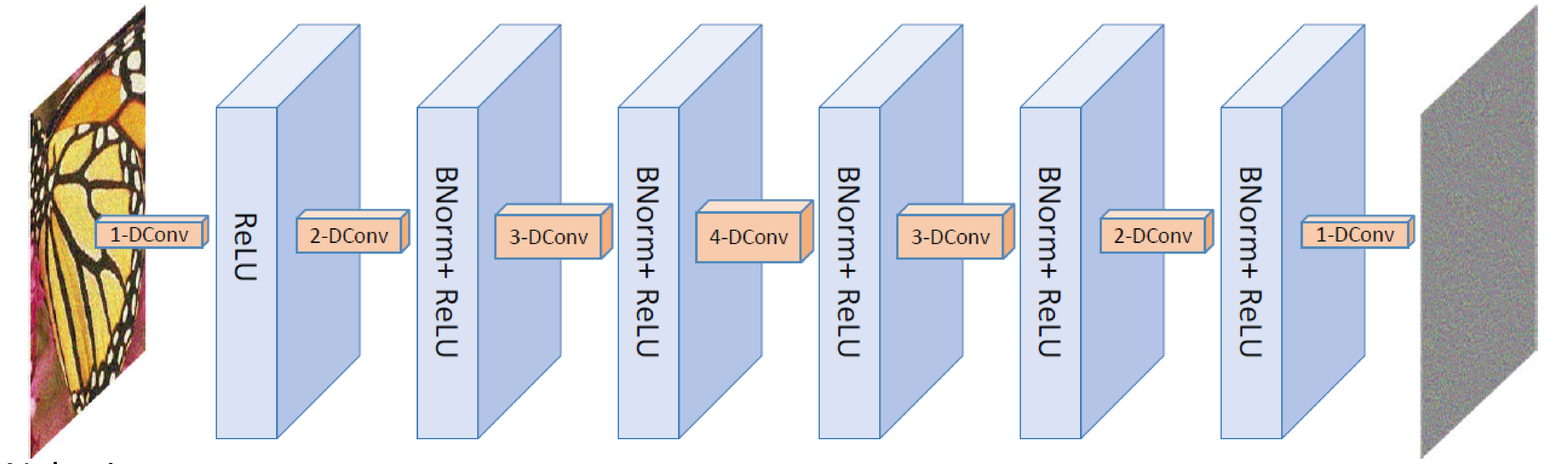
$$min_{\boldsymbol{x},\boldsymbol{z}} \ \|\boldsymbol{y}-\boldsymbol{H}\boldsymbol{x}\|_2^2+\lambda\cdot R(\boldsymbol{z})+\eta\|\boldsymbol{z}-\boldsymbol{x}\|_2^2$$

Solving $\boldsymbol{x}$ and $\boldsymbol{z}$ alternatively and iteratively

(a) $min_{\boldsymbol{x}} \ \|\boldsymbol{y}-\boldsymbol{H}\boldsymbol{x}\|_2^2+\eta\|\boldsymbol{z}-\boldsymbol{x}\|_2^2$ % Quadratic regularized least- squares problem

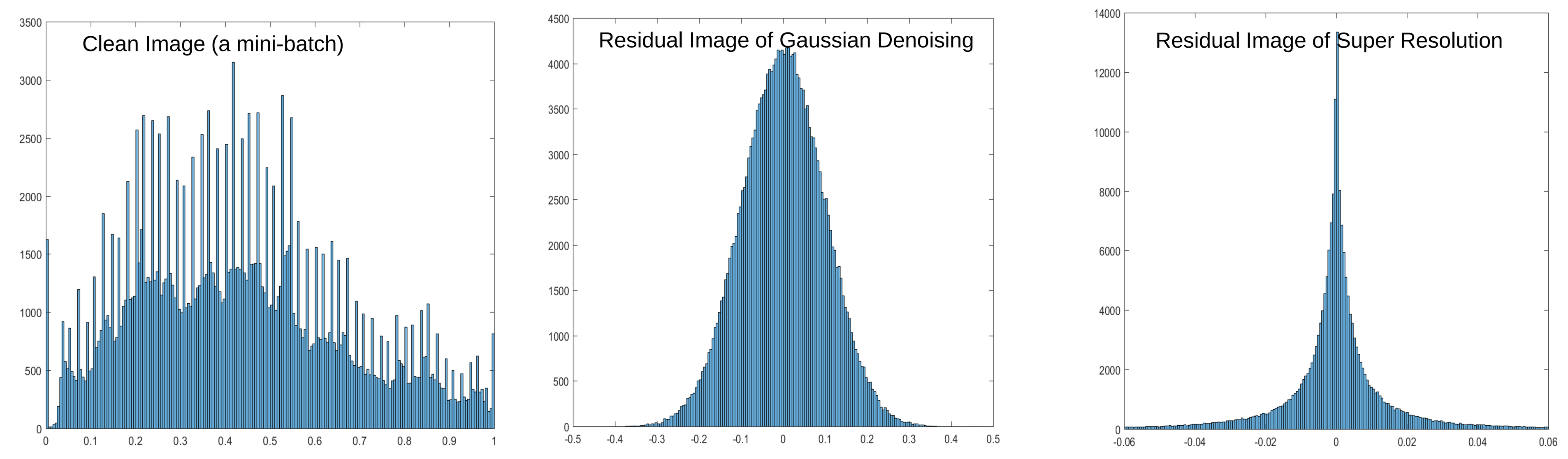
(b) $min_{\boldsymbol{z}} \ \eta\|\boldsymbol{x}-\boldsymbol{z}\|_2^2+\lambda\cdot R(\boldsymbol{z})$ % Denoising sub-problem

Network Architecture



Note that “s-DConv” denotes s-dilated convolution, s = 1, 2, 3 and 4; “BNorm” represents batch normalization; “ReLU” is the rectified linear units (max(·, 0)).

Design Rationale and Training Details



- ***The residual image of Gaussian denoising has a simple Gaussian distribution.***
- ***Batch normalization and residual learning are beneficial to each other*** [1].
- Using dilated filter to enlarge receptive field.
- Using training samples with small size to help avoid boundary artifacts.
- Learning specific denoiser model with small interval noise levels.

Experiments

Image Denoising

Table: The averaged PSNR(dB) results of different methods on BSD68 dataset.

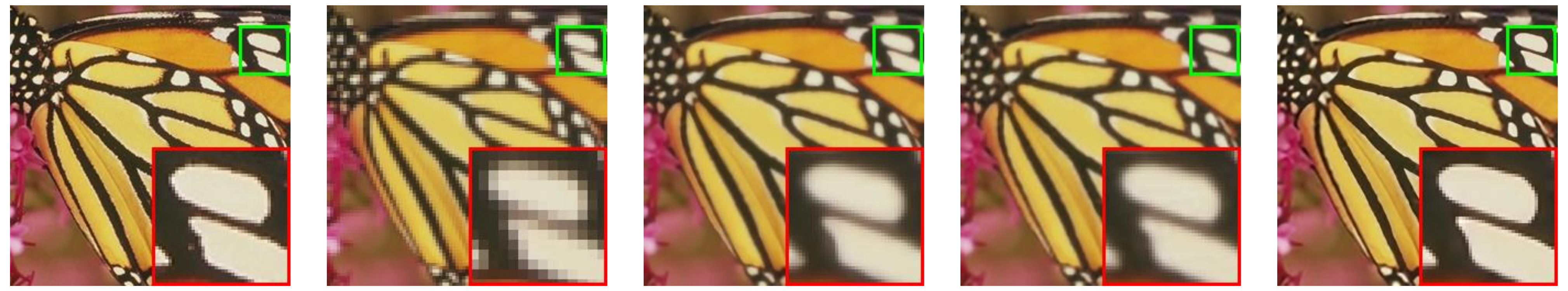
Methods	BM3D	WNNM [2]	TNRD	Proposed
15	31.07	31.37	31.42	**31.73**
25	28.57	28.83	28.92	**29.23**
50	25.62	25.87	25.97	**26.23**

Image Deblurring

(a) Blurry and noisy image (b) IDDBM3D (26.95dB) (c) NCSR (27.50dB) (d) MLP (28.91dB) (e) Proposed (29.78dB)

Figure: Image deblurring performance comparison (the blur kernel is Gaussian kernel with standard deviation 1.6, the noise level is 2).

Image Super-Resolution



(a) Ground-truth (b) Zoomed LR image (c) SRCNN (24.46dB) (d) VDSR (24.73dB) (e) Proposed (29.32dB)

Figure: Single image super-resolution performance comparison for *Butterfly* image from Set5 (the blur kernel is 7×7 Gaussian kernel with standard deviation 1.6, the scale factor is 3). The proposed deep CNN denoiser prior based optimization method can super-resolve LR image by tuning the blur kernel and scale factor without training.

Reference

[1] K. Zhang, W. Zuo, Y. Chen, D. Meng and L. Zhang, "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising“, in IEEE Transactions on Image Processing, vol. 26, no. 7, pp. 3142-3155, July 2017.

[2] S. Gu, L. Zhang, W. Zuo and X. Feng, “Weighted nuclear norm minimization with application to image denoising”, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014: 2862-2869.

Code: https://github.com/cszn/ircnn