Patch Group Based Nonlocal Self-Similarity Prior Learning for Image Denoising

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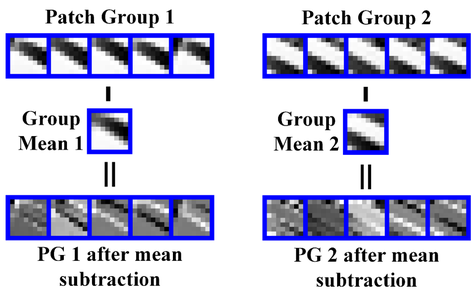
Motivation

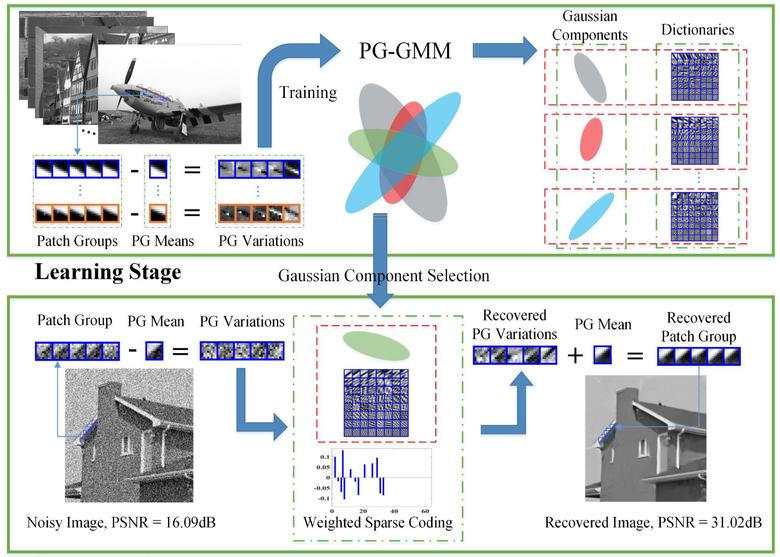
The use of image nonlocal self-similarity (NSS) prior has significantly enhanced the denoising performance. However, most existing methods only exploit the NSS of input degraded images, while ignoring the NSS of clean natural images.



The formation of two patch groups (PG) sharing similar PG variations

In this paper, we propose a patch group (PG) based NSS prior learning scheme to learn explicit NSS models from natural images for high performance denoising. The proposed PG Prior based Denoising (PGPD) algorithm is highly efficient, and effective in edge preservation.

The PGPD Method



Patch Group Based GMM

$$\ln \mathcal{L} = \sum_{n=1}^{N} \ln\Big(\sum_{k=1}^{K} \pi_k \prod_{m=1}^{M} \mathcal{N}(\overline{\mathbf{x}}_{n,m} | \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)\Big)$$

Model Selection

$$P(k|\overline{\mathbf{Y}}) = \frac{\prod_{m=1}^{M} \mathcal{N}(\overline{\mathbf{y}}_m | \mathbf{0}, \boldsymbol{\Sigma}_k + \sigma^2 \mathbf{I})}{\sum_{l=1}^{K} \prod_{m=1}^{M} \mathcal{N}(\overline{\mathbf{y}}_m | \mathbf{0}, \boldsymbol{\Sigma}_l + \sigma^2 \mathbf{I})}$$

Weighted Sparse Coding With Closed-form Solution

$$\min_{\boldsymbol{\alpha}} \|\overline{\mathbf{y}}_m - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \|\mathbf{w}^T \boldsymbol{\alpha}\|_1$$

$$\hat{\boldsymbol{\alpha}} = \mathrm{sgn}(\mathbf{D}^{\mathrm{T}} \overline{\mathbf{y}}_m) \odot \max(|\mathbf{D}^{\mathrm{T}} \overline{\mathbf{y}}_m| - \mathbf{w}/2, 0)$$

PSNR

σ	BM3D	LSSC	EPLL	NCSR	WNNM	PGPD
10	34.21	34.39	33.99	34.31	34.53	34.19
20	30.95	31.03	30.75	30.95	31.20	30.95
30	29.13	29.11	28.92	29.03	29.37	29.13
40	27.69	27.80	27.62	27.71	28.05	27.88
50	26.80	26.78	26.61	26.69	27.08	26.89
75	25.04	24.90	24.81	24.79	25.30	25.11
100	23.78	23.59	23.59	23.49	24.04	23.85

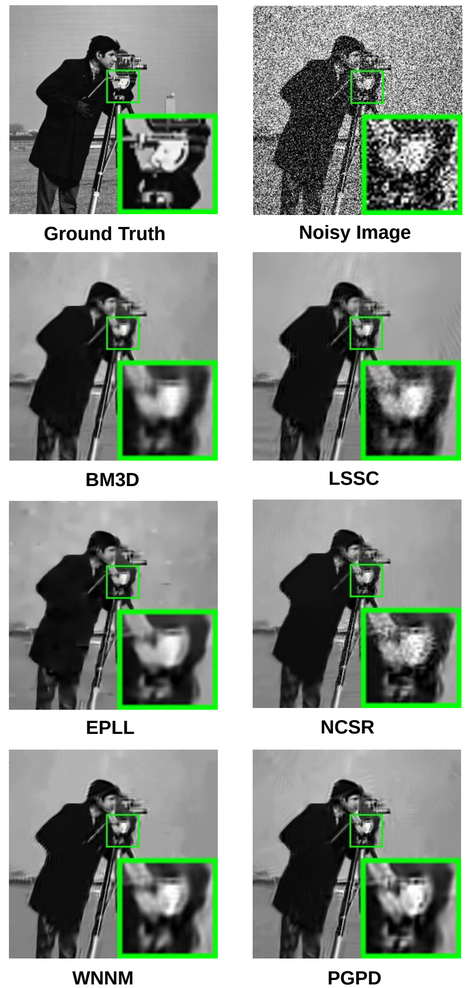
Table 1. Average PSNR (dB) on 20 testing images by different methods.

Speed

σ	BM3D	LSSC	EPLL	NCSR	WNNM	PGPD
10	0.67	186.90	38.47	126.43	84.34	8.00
20	0.70	184.21	38.47	156.14	84.70	8.09
30	0.70	212.07	38.55	149.31	155.75	8.47
40	0.67	209.13	38.51	346.91	157.35	9.80
50	0.87	221.36	40.21	326.93	119.47	9.91
75	0.89	240.75	40.91	258.04	179.30	11.73
100	0.90	257.25	42.80	252.74	191.32	11.78

Table 2. Running time (sec.) of different methods to process a 256 x 256 image.

Visual Quality



Partial References

M. Elad and M. Aharon. Image denoising via sparse and redundant representations over learned dictionaries. Image Processing, IEEE Transactions on, 15(12):3736–3745, 2006.
A. Buades, B. Coll, and J. M. Morel. A non-local algorithm for image denoising. CVPR, pages 60–65, 2005.
D. Zoran and Y. Weiss. Natural images, Gaussian mixtures and dead leaves. NIPS, pages 1736–1744, 2012.
G. Yu, G. Sapiro, and S. Mallat. Solving inverse problems with piecewise linear estimators: From Gaussian mixture models to structured sparsity. Image Processing, IEEE Transactions on, 21(5):2481–2499, 2012.
J. Wright, Y. Ma, J. Mairal, G. Sapiro, T. S. Huang, and S. Yan. Sparse representation for computer vision and pattern recognition. Proceedings of the IEEE, 98(6):1031–1044, 2010.
K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian. Image denoising by sparse 3-D transform-domain collaborative filtering. Image Processing, IEEE Transactions on, 16(8):2080–2095, 2007.
D. Zoran and Y.Weiss. From learning models of natural image patches to whole image restoration. ICCV, pages 479–486, 2011.
W. Dong, L. Zhang, G. Shi, and X. Li. Nonlocally centralized sparse representation for image restoration. Image Processing, IEEE Transactions on, 22(4):1620–1630, 2013.
S. Gu, L. Zhang,W. Zuo, and X. Feng.Weighted nuclear norm minimization with application to image denoising. CVPR, pages 2862–2869, 2014.
J. Mairal, F. Bach, J. Ponce, G. Sapiro, and A. Zisserman. Non-local sparse models for image restoration. ICCV, pages 2272–2279, 2009.