JOINT DEMOSAICING AND DENOISING OF NOISY BAYER IMAGES WITH ADMM

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PROBLEM

Bayer image $b \in R^n$ and RGB $x = [r^T, g^T, b^T]^T \in R^{3n}$. The image formation model is

$$b = Ax + \eta \tag{1}$$

where $A \in R^{n\times 3n}$ is the mosaic matrix which down samples RGB image x to Bayer image b, and $\eta \in R^n$ is the noise vector.

Joint demosaicing and denoising can be viewed as the inverse problem of (1)

$$\min_x \|Ax - b\|_2^2 + T(x) \tag{2}$$

where $T(x)$ represents the prior functions.

This is a difficult problem due to limited information, that is only $1/3$ pixels are known.

REFERENCES

[1] F. Heide, et. al. FlexISP: a flexible camera image processing framework. In *ACM Transactions on Graphics (TOG), 2014*

[2] M. Gharbi, et al. GraphTrack: Deep joint demosaicking and denoising. In *ACM Transactions on Graphics (TOG), 2016*

[3] Rudin, et. al. Nonlinear total variation based noise removal algorithms in *Physica D: Nonlinear Phenomena, 1992*

[4] K. Dabov, et. al. Color image denoising via sparse 3D collaborative filtering with grouping constraint in luminance-chrominance space in *IEEE International Conference on Image Processing (ICIP), 2007*

[5] F. Heide, et. al. High-quality computational imaging through simple lenses in *ACM Transactions on Graphics (TOG), 2013*

[6] K. Dabov, et. al. High-quality linear interpolation for demosaicing of Bayer-patterned color images in *IEEE International Conference onAcoustics, Speech, and Signal Processing (ICASSP), 2004*

METHOD

The image recovery model is specialized as

$$\min_x \|Ax - b\|_2^2 + \lambda_{tv}\|\nabla x\|_1 + \lambda_{bm3d} bm3d(x) + \lambda_{cc}\|Cx\|_1 + \lambda_{dm} demosaic(x) \tag{3}$$

The above equation consists of one data term and four priors: total variation [3], bm3d denoising term [4], cross-channel prior [5] and demosaicing prior [6].

Suppose we have a minimization problem with J terms

$$\min_{z\in R^d} \sum_{j=1}^{J} g_j(H^{(j)}z) \tag{4}$$

where $g_j : R^{p_j} \to R$ are functions with closed form, $H^{(j)} \in R^{p_j \times d}$ are matrices and $p = p_1 + \cdots + p_J$. The general steps solving problem (4) are

1. Initialize u_0, d_0, μ with zero vectors.
2. Start iteration

1: $\zeta_k^{(j)} \leftarrow u_k^{(j)} + d_k^{(j)}, \quad j = 1, \cdots, J$
2: $\gamma_k \leftarrow \sum_{j=1}^{J}(H^{(j)})^T \zeta_k^{(j)}$
3: $z_{k+1} \leftarrow [\sum_{j=1}^{J}((H^{(j)})^T H^{(j)})]^{-1}\gamma_k$
4: **for** $j = 1$ to J **do**
5: $\quad \nu_k^{(j)} \leftarrow H^{(j)} z_{k+1} - d_k^{(j)}$
6: $\quad u_{k+1}^{(j)} \leftarrow \text{argmin}_v \frac{\mu}{2}\|v - \nu_k^{(j)}\|_2^2 + g_j(v)$
7: **end for**
8: $d_{k+1}^{(j)} \leftarrow d_k^{(j)} - (H^{(j)} z_{k+1} - u_{k+1}^{(j)}), \quad j = 1, \cdots, J$

Line 6 corresponds to a restoration problem with v as the data term and $g_j(v)$ as the prior term, which suggests ADMM split a complicated minimization problem with multiple prior terms into multiple simple minimization problems with only one prior term.

CONTRIBUTIONS

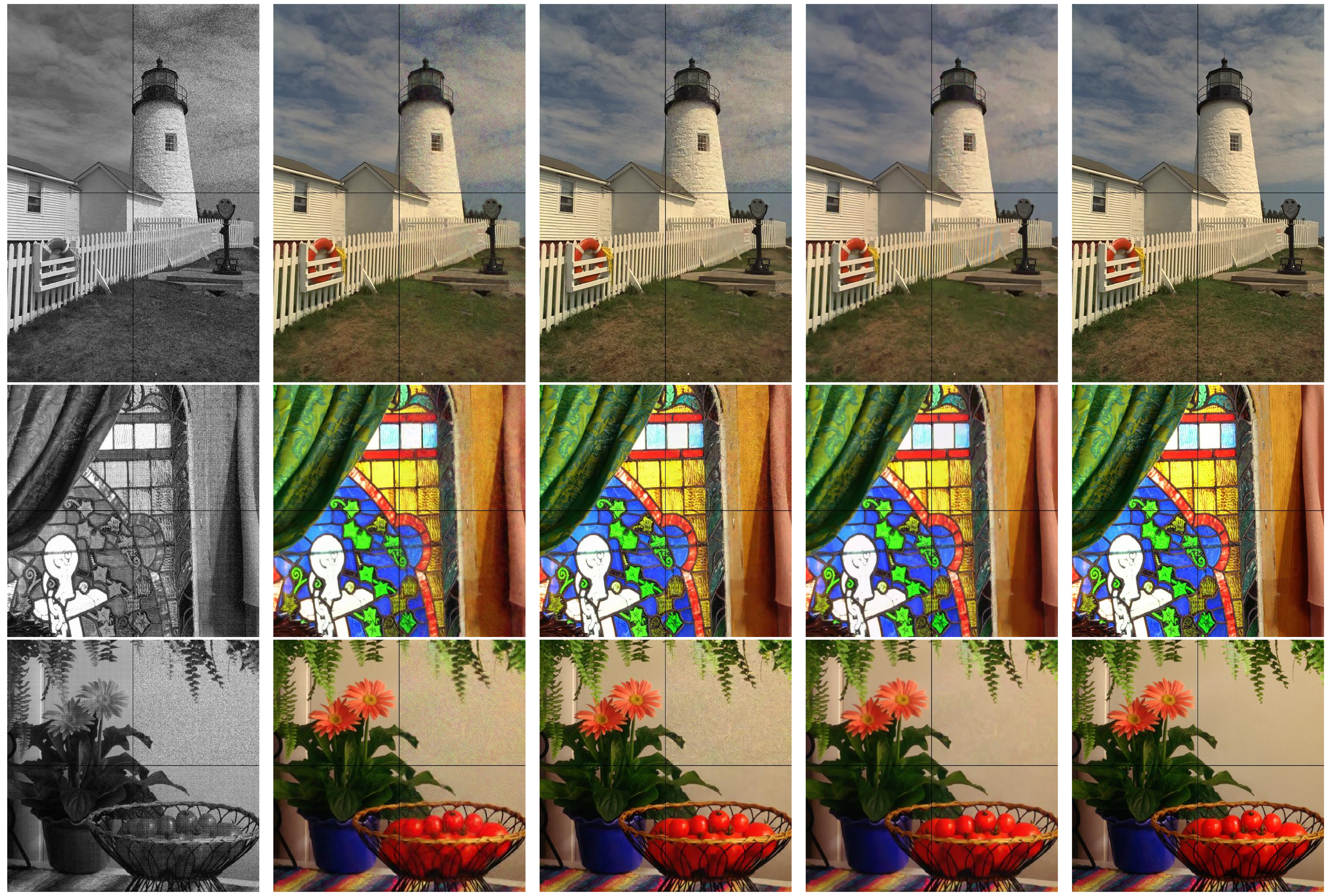
We improve demosaicing and denoising by

1. Introducing hidden priors in minimization model solved by ADMM
2. Combing multiple effective priors
3. Producing results with better performance and robustness to noise

SOURCE CODE

The source code is available at github: https://github.com/TomHeaven/Joint-Demosaic-and-Denoising-with-ADMM.

RESULTS



BayerNoisy FlexISP DeepJoint ADMM(Ours) Groundtruth

Fig. 1 Visual Results. The first row and the last two rows of images are from Kodak and McMaster datasets, respectively. Each image is divided into four rectangular parts: Top-left, bottom-left, bottom-right and top-right correspond to noise levels $\sigma = 0, 5, 15, 25$, respectively.

Table 1 Average PSNR Comparison on Two Datasets (dB)

Dataset	Noise Level	FlexISP [1]	Deep Joint [2]	ADMM (Ours)	Dataset	Noise Level	FlexISP [1]	Deep Joint [2]	ADMM (Ours)
Kodak (24 images)	0	**34.98**	33.88	31.63	Mc-Master (18 images)	0	**35.18**	32.49	32.66
	5	31.31	**33.07**	31.60		5	31.17	32.01	**32.63**
	15	26.67	**30.40**	30.16		15	26.55	29.89	**30.50**
	25	23.90	25.88	**28.38**		25	23.73	26.13	**28.20**