A Review of an Old Dilemma: Demosaicking First, or Denoising First?

Qiyu Jin, Gabriele Facciolo, and Jean-Michel Morel

(1) Inner Mongolia University, 010021 Hohhot, China, (2) Centre Borelli, ENS Paris-Saclay, France

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Objective

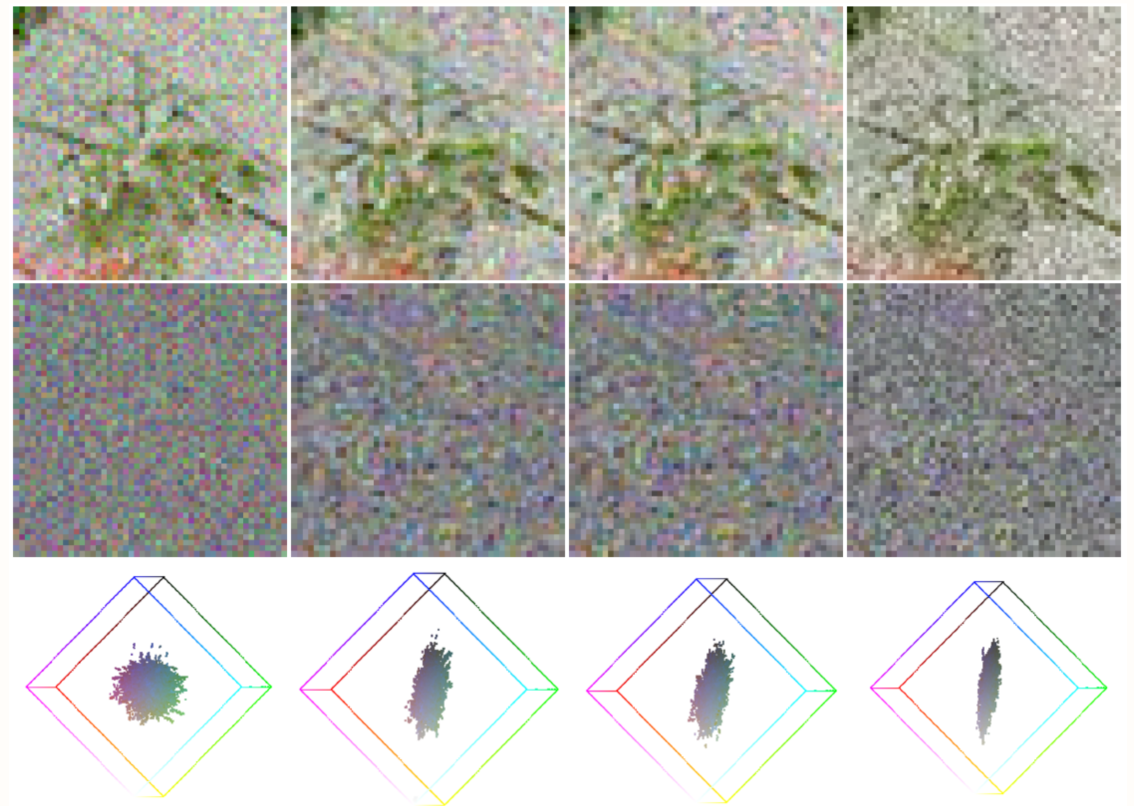
- Review and analyze advantages and drawbacks of different strategies of Denoising and Denosaicking.
- Analyze the demosaicking noise.
- Find the best way to reconstruct full color images from a noisy mosaic.

Strateties of demosaicking and denoising

3 strateties are considered:

1. **Joint denoising/demosaicking methods:**
   Most of Joint denoising/demosaicking methods based on machine learning and deep learning, which can handle a range of noise levels, but unlike traditional methods, they fail outside the trained range.
2. **Denoising then demosaicking methods:**
   Disadvantage: some details might be lost after denoising, checkerboard effects.
   Advantage: i.i.d. white Gaussian noise, all classic denoising and demosaicking algorithms can be used.
3. **Demosaicking then denoising methods:**
   Disadvantage: chromatic and spatial correlations introduced by the demosaicking in the raw noise.
   Advantage: more details preserved and checkerboard effects avoided.

Analyze the demosaicked noise



(a) AWG (b) HA (c) MLRI (d) RCNN

Figure 1: AWG noise image and demosaicking noise with standard deviation $\sigma = 20$ for respectively HA[1], MLRI[2], RCNN[3]. Last row: the color spaces (in standard (R,G,B) Cartesian coordinates) of each noise, presented in their projection with maximal area.

Table 1: Variance and covariance of (R, G, B) and (Y, U, V) (each first row) and the corresponding correlations (each second row) between pixels (i, j) and $(i+s, j+t)$, $s, t = 0, 1, 2$ first for AWGN (a) with standard deviation $\sigma = 20$, then for its demosaicked versions and RCNN (c).

	(i,j)	(i,j+1)	(i,j+2)	(i+1,j)	(i+1,j+1)	(i+1,j+2)	(i+2,j)	(i+2,j+1)	(i+2,j+2)
R	400.6	0.6	0.4	0.7	0.1	0.7	0.3	0.2	0.8
G	401.7	0.5	1.1	0.1	0.3	0.9	1.0	0.6	0.4
B	400.2	1.2	0.1	0.5	0.6	0.0	1.9	0.3	1.9
Y	399.6	1.1	0.1	0.3	0.1	0.9	0.2	0.5	1.2
C_1	401.5	0.1	0.8	0.6	0.3	0.3	0.9	0.5	1.3
C_2	401.4	0.2	1.8	0.9	0.2	1.0	0.6	0.2	0.2

(a) AWG noise

	(i,j)	(i,j+1)	(i,j+2)	(i+1,j)	(i+1,j+1)	(i+1,j+2)	(i+2,j)	(i+2,j+1)	(i+2,j+2)
R	359.9	47.8	5.0	51.9	21.8	17.8	5.1	19.4	9.2
G	354.8	32.6	4.4	36.3	5.8	8.4	6.4	8.8	0.6
B	356.0	49.6	6.3	53.7	23.6	18.8	7.3	19.4	9.2
Y	972.3	69.0	20.8	76.4	3.6	18.6	28.9	17.3	2.2
C_1	55.1	33.8	15.3	36.0	26.1	14.6	19.0	16.6	11.8
C_2	43.3	27.3	12.3	29.4	21.5	11.7	16.0	13.7	9.4

(c) RCNN

Table 2: Covariances (each first row) and *correlations* (each second row) of the three color channels (R, G, B) of the demosaicked noise, when the initial CFA white noise satisfies $\sigma_0 = 20$.

	R	G	B
R	361.42	224.39	201.41
	1.0000	*0.6826*	*0.5501*
G	224.39	298.94	216.86
	0.6826	*1.0000*	*0.6512*
B	201.41	216.86	370.92
	0.5501	*0.6512*	*1.0000*

(a) MLRI

	R	G	B
R	359.90	320.44	302.85
	1.0000	*0.8967*	*0.8461*
G	320.44	354.83	299.85
	0.8967	*1.0000*	*0.8437*
B	302.85	299.85	355.99
	0.8461	*0.8437*	*1.0000*

(b) RCNN

Table 3: Comparison in CPSNR(dB) of average restoration performance between DN&DM and DM&DN for a fixed level of noise $\sigma_0 = 20$. The best result of each column is marked with a box. The best result of each line is in red and the second best one is in green.

DN	Algorithm	HA	RI	MLRI	ARI	RCNN
CBM3D[4]	DN&DM	28.11	28.45	27.97	28.69	27.27
	DM&DN	28.15	28.46	27.95	28.70	27.28
	DM&1.5DN	$\boxed{29.24}$	$\boxed{29.32}$	$\boxed{29.22}$	$\boxed{29.36}$	$\boxed{29.41}$
nlBayes[5]	DN&DM	28.17	28.17	28.17	28.18	28.28
	DM&DN	28.67	28.99	28.57	29.21	28.02
	DM&1.5DN	$\boxed{29.29}$	$\boxed{29.26}$	$\boxed{29.22}$	$\boxed{29.31}$	$\boxed{29.36}$

The model of the demosaicked noise depends on the choice of the demosaicking algorithm DM. Fig. 1 shows a strong (R, G, B) correlation, which is caused by the "tendency to grey" of all demosaicking algorithms. Assuming that the demosaicked noisy pixel components (denoted $\tilde{e}_R, \tilde{e}_G, \tilde{e}_B$) have a correlation coefficient close to 1 then we have (see Table 1)

$$Y = \frac{\tilde{e}_R + \tilde{e}_G + \tilde{e}_B}{\sqrt{3}} \sim \sqrt{3}\, N(0, \sigma_0).$$

Observations and proposed strategy

- Demosaicked noise is correlated and have higher standard deviation in the luminance component
- This is caused by the "tendency to grey" of demosaicking algorithms
- **We propose to denoise the demosaicked image using a higher** σ (denoted $\mathrm{DM\&1.5DN}$)
- This strategy can be applied to many demosaicking and denoising algorithms

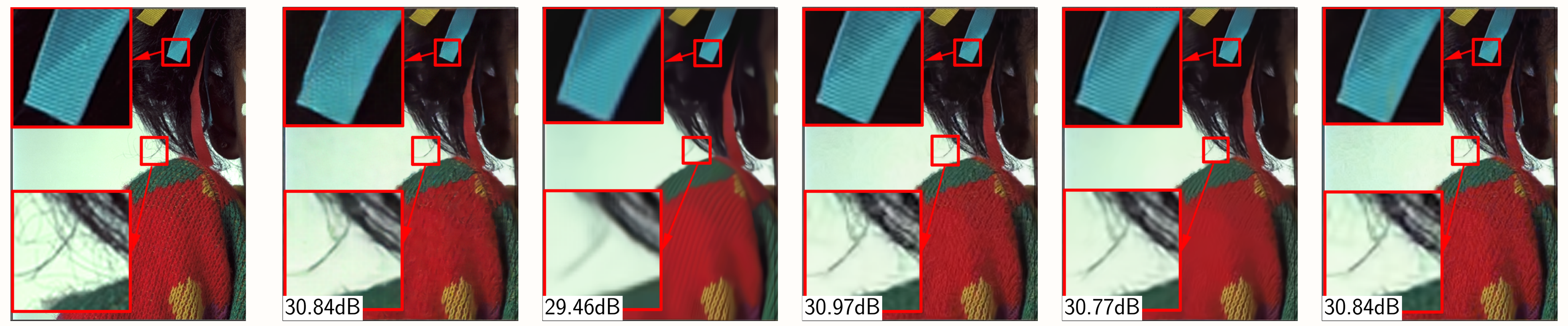
Experimental evaluation

Table 4: Comparison of the results (CPSNR in dB) between different denoising and demosaicking methods for the **Imax** image set. The best result of each line is in red, the second best one is in green and the third best one is in blue.

	DN&DM						DM&1.5DN			
σ	BM3D + HA	BM3D + RCNN	Park + HA	Park + RCNN	PCA + DLMM	PCA + RCNN	RCNN + CBM3D	RCNN + nlBayes	MLRI + CBM3D	JCNN
1	34.63	38.53	32.74	35.37	33.99	37.52	38.36	38.42	36.52	38.59
5	33.43	35.62	31.57	32.86	32.69	34.87	35.39	35.29	34.60	33.48
10	31.84	32.92	29.62	30.06	30.73	31.89	32.75	32.59	32.36	33.09
20	29.22	29.55	26.82	26.86	27.57	27.99	29.41	29.25	29.22	29.79
40	25.50	25.51	23.90	23.86	23.50	23.57	25.52	25.09	25.39	–
60	21.55	21.34	21.78	21.75	20.89	20.89	22.78	22.31	22.63	–
Av	28.09	28.88	26.45	26.89	26.71	27.53	28.99	28.72	28.58	–

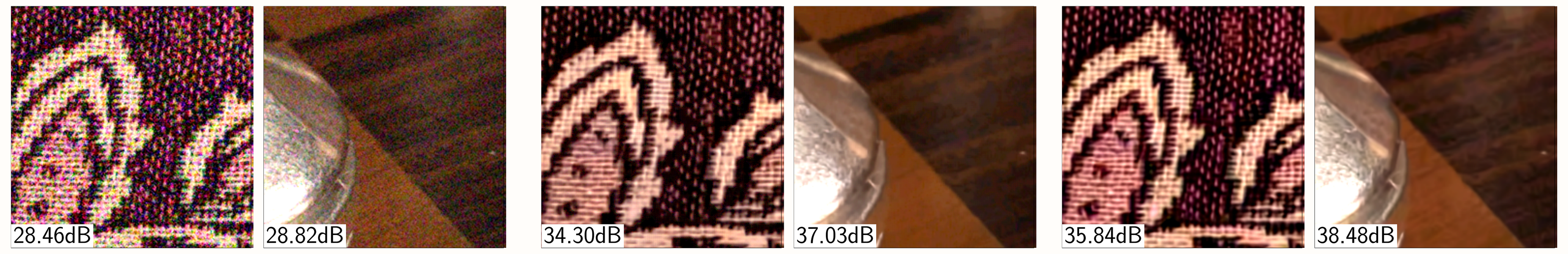
Table 5: Comparison of the results (CPSNR in dB) between different denoising and demosaicking methods for the **Kodak** image set. The best result of each line is in red, the second best one is in green and the third best one is in blue.

	DN&DM						DM&1.5DN			
σ	BM3D + HA	BM3D + RCNN	Park + HA	Park + RCNN	PCA + DLMM	PCA + RCNN	RCNN + CBM3D	RCNN + nlBayes	MLRI + CBM3D	JCNN
1	34.70	40.55	34.35	40.36	38.19	39.12	40.98	40.98	38.52	41.15
5	32.84	34.89	32.54	34.87	34.99	35.42	36.55	36.42	35.71	34.13
10	30.34	30.93	30.10	30.85	31.83	32.01	33.36	33.18	32.94	33.27
20	27.59	27.70	27.28	27.42	28.11	28.14	29.98	29.87	29.70	29.95
40	24.79	24.78	24.88	24.88	24.15	24.08	26.71	26.29	26.44	–
60	22.58	22.55	23.21	23.19	21.77	21.70	24.42	23.93	24.16	–
Av	27.47	28.35	27.41	28.36	27.96	28.09	30.19	29.93	29.64	–



Ground Truth | JCNN[6] | BM3D+RCNN[7] (DN&DM) | RCNN+BM3D (DM&1.5DN) | RCNN+nlBayes (DM&1.5DN) | MLRI+BM3D (DM&1.5DN)

Figure 2: Demosaicking and denoising results on an image from the Kodak dataset with $\sigma = 20$.



noisy demosaicked | DN&DM | DM&1.5DN

Figure 3: Details of a real images (enhanced contrast) from the SIDD [8] dataset. From left to right: noisy input (demosaicked), BM3D+RCNN , and RCNN+CBM3D.

Conclusions and discussion

- Demosaicking First, or Denoising First? The answer is that Demosaicking First is better than Denoising First, but the DN step should set the noise parameter with $1.5\sigma_0$.
- **The** $\mathrm{DM\&1.5DN}$ **scheme.** Demosaicking DM is done by a fast algorithm RCNN [3] followed by CBM3D denoising 1.5DN with noise parameter equal to $1.5\sigma_0$, which performs best in terms of quality and speed.
- **Visual quality.** The DM&DN schemes allowed a better preservation of fine structures often smoothed by the DN&DM schemes(Figs. 2 and 3).
- We anticipate joint demosaicking and denoising methods obtained by deep learning to win the end game when they become more compact or rapid.

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