Image Denoising with Signal Dependent Noise Using Block Matching and 3D Filtering

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Abstract. In this paper, we propose a new method for image denoising. We use block matching 3D filtering (BM3D) to denoise the noisy image, and then denoise the noisy residual and merge this denoised residual into the denoised image. We can perform another BM3D to this merged image if the noise-level is still higher than a threshold. Our method performs similarly as the BM3D for Gaussian white noise, and it outperforms the BM3D, Poisson-Gaussian BM3D (PGBM3D), and Bivariate shrinking (BivShrink) for nearly all cases in our experiments for signal dependent noise. The method does not assume the noise to be Gaussian alone, and it works well for a mixture of Gaussian and signal-dependent noise. However, the computational complexity of the new method is twice and at most three-times that of the standard BM3D for image denoising.

Keywords: Image denoising, Block matching 3D filtering (BM3D), signal-dependent noise.

1 Introduction

Digital images are often contaminated by different types of noise, including Gassian white noise, salt-and-pepper noise, Laplacian noise, signal dependent noise, impulse noise, and so forth. There are a number of trade-offs in reducing noise in an image. For example, whether sacrificing some image details is acceptable if we want to remove more noise in the image. In order to make better decision, the characteristics of the noise and the details in the images should also be taken into account.

In existing literature, the majority of denoising methods is dealing with Gaussian white noise, which can be modeled as:

$$B = A + \sigma_n Z, \tag{1}$$

where A is the noise-free image and B the image corrupted with Gaussian white noise, Z has a normal distribution N(0; 1) and σ_n is the noise standard deviation. There are a number of methods to deal with this kind of noise. Fathi and Naghsh-Nilchi [1] proposed an efficient image denoising method based on a new adaptive wavelet packet thresholding function. Chatterjee and Milanfar [2] studied patch-based

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near-optimal image denoising. Rajwade et al. [3] worked on image denoising using the higher order singular value decomposition. Motta et al. [4] proposed the iDUDE framework for gray scale image denoising. Miller and Kingsburg [5] studied image denoising using derotated complex wavelet coefficients. Sendur and Selesnick [6] proposed a bivariate wavelet denoising technique for images. Dabov et al. [7] proposed a block matching 3D filtering (BM3D) technique for image denoising, which is the state-of-the-art in image denoising. Mäkitalo and Foi [8] developed a Poisson-Gaussian BM3D (PGBM3D) method for denoising. Chen and Kegl [9] proposed an Image denoising technique using complex ridgelets. Chen et al. [10] developed a wavelet-based image denoising method using three scales of dependency in wavelet coefficients. Chen et al. [11] invented an image denoising method using neighbouring wavelet coefficients. Chen et al. [12] developed an image denoising method with neighbour dependency and customized wavelet and threshold. Cho and Bui [13] proposed a multivariate statistical modeling technique for image denoising using wavelet transforms. Cho et al. [14] also studied Image denoising based on wavelet shrinkage using neighbour and level dependency.

Even though Gaussian white noise is well studied, there exist other kinds of noise in real-life images. For example, CMOS and CCD sensors are two special devices that suffer from noise. In CMOS sensors, there exists fixed pattern noise and a mixture of independent additive and multiplicative Gaussian noise. We formulate this kind of noisy image B as:

$$B = A + (k_0 + k_1 A)Z \tag{2}$$

where (k_0, k_1) are two parameters to determine the noise levels, A is the noise-free image, and Z is the Gaussian white noise with N(0,1) distribution. Only a few papers exist in the literature for reducing this kind of noise ([15], [16], [17]). Hirakawa and Parks [15] proposed an image denoising method for signal-dependent noise. Bosco et al. [16] studied signal-dependent raw image denoising using sensor noise characterization via multiple acquisitions. Goossens et al. [17] developed a wavelet domain image denoising technique for non-stationary noise and signal-dependent noise.

In this paper, we propose a new method for reducing this kind of noise. Our method is based on the block matching 3D filtering (BM3D) method [7], which is the state-of-the-art in image denoising. We perform the BM3D to the noisy image, and then conduct the BM3D to the noise residual. We merge these two denoised images and perform another BM3D to this merged image. Our new method is very simple, but it outperforms the standard BM3D [7], BivShrink [6] and Poisson-Gaussian BM3D (PGBM3D) [8] in term of peak signal to noise ratio (PSNR) for nearly all cases in our experiments for the mixture noise model discussed in this paper.

2 Proposed Method

In this paper, we propose a new method to reduce the noise in a noisy image. Our method deals with a mixture of the Gaussian white noise and the signal-dependent noise. Most denoising methods reduce the noise from the noisy images and only keep the denoised images. However, in our method, we denoise the noisy residual and merge this denoised residual into the denoised image. In this way, we can achieve better denosing results because more fine features can be retained. We can still perform another denoising operation to this merged image if the noise-level is still higher than a threshold. The noise variance σ_n can be approximated as [18]:

$$\sigma_n = \frac{median(|\, y_{1i} \,|)}{0.6745}, \quad y_{1i} \in \text{subband } HH_1. \tag{3}$$

where HH_1 is the finest scale of wavelet coefficient subband. We only need to perform the wavelet transform on the noisy image for one decomposition scale in order to estimate σ_n.

In order to achieve better denoising results, we choose the BM3D algorithm [7] to reduce noise in our proposed method. The BM3D algorithm is divided in two major steps. The first step estimates the denoised image using hard thresholding during the collaborative filtering. The second step is based on both the original noisy image and the basic estimate obtained in the first step.

The collaborative filtering can be summarized as follows:

1. Locate the image patches similar to a given image patch and grouping them in a 3D block.
2. 3D linear transform of the 3D block.
3. Shrink the transform spectrum coefficients.
4. Inverse 3D transformation.

As a consequence, this 3D filtering can filter out all 2D image patches in the 3D block simultaneously. By reducing the noise, the collaborative filtering retains the finest details shared by grouped blocks and at the same time it preserves the essential unique features of each individual block. The filtered blocks are then returned to their original positions. Because there are overlapping in these blocks, we can obtain many different estimates for each pixel. Aggregation is a particular averaging procedure, which is exploited to take advantage of this redundancy in each 3D block.

In summary, we list the steps of our new method in this paper as follows:

1. Given the noisy image B, estimate the noise variance σ_n^1 from B according to equation (3).
2. Perform BM3D to B as $B_1 = BM3D(B, \sigma_n^1)$. Set $\tilde{B} = 255 \times B_1$ since BM3D scales the output image to the range of [0,1].
3. Get the residual image $B_2 = B - \tilde{B}$, and estimate the noise variance σ_n^2 from B_2 according to equation (3).
4. Perform BM3D as $C = BM3D(B_2, \sigma_n^2)$.
5. Normalize $C_1 = \tilde{B} + C \times \frac{mean(B_2)}{mean(C)}$. Estimate noise variance σ_n^3 from C_1 according to equation (3).
6. If σ_n^3>T (T=1.0), then $D = BM3D(C_1, \sigma_n^3 \times \sigma_n^2 / 2)$. Here we use a bigger noise variance for BM3D because this can generate better denoising results.

7. Output $A = 255 \times D$ since BM3D scales the output image to the range of [0,1]. Stop.
8. If $\sigma_n^3 \leq T$, then output $A = \tilde{B}$. Stop.

The major contribution of this paper is the following. We have taken advantage of the BM3D method, which is the state-of-the-arts in image denoising, for a mixture of the Gaussian white noise and the signal-dependent noise. Our new method can retain more fine features in the denoised images than other existing denoising techniques for image denoising. Experimental results show that our proposed method is similar to the BM3D method for Gaussian white noise, and it is better than the BivShink [6], the BM3D [7], and the Poisson-Gaussian BM3D (PGBM3D) [8] for the mixture noise model for nearly all cases in our experiments.

The major limitation of our proposed method is that it is slower than the standard BM3D since it calls the BM3D for twice and at most three times. We are sacrificing some computation time in exchange for better image quality.

3 Experimental Results

We conducted a number of experiments in order to demonstrate the power of our proposed method in this paper. We tested our method with four grey-scale images: Fingerprint, House, Lena, and Pepper. These images are frequently used in other denoising papers in the literature. We compared our method with the BivShink, the BM3D, and the Poisson-Gaussian BM3D (PGBM3D). We considered both the Gaussian white noise and the signal-dependent noise in our experiments. Tables 1-4 tabulate the peak signal to noise ratio (PSNR) of the denoising methods mentioned above for the seven images, respectively. The PSNR is defined as

$$PSNR = 10\log_{10}\left(\frac{M \times N \times 255^2}{\sum_{i,j}(B(i,j) - A(i,j))^2}\right) \tag{4}$$

where $M \times N$ is the number of pixels in the image, and A and B are the noise-free and denoised images. Fig. 1 shows the original noisy images, and the images generated by BivShrink, BM3D, PGBM3D, and our proposed method. It can be seen that our proposed method is comparable to BM3D for Gaussian white noise, and it is nearly always better than all other methods compared in this paper for signal-dependent noise. It should be pointed out that the standard BM3D is better than our new method in one case for the image Fingerprint. However, such cases are really rare in our experiments conducted in this paper. The PSNR improvement of our proposed method over standard BM3D sometimes can reach 5 dB. This indicates that our proposed denoising method in this paper is a good choice in enhancing real-life images.

In standard BM3D, the noise variance σ_n is a known parameter for the noisy image. We estimate it by using equation (2) in this paper. Since we only need to perform the wavelet transform for one decomposition scale, the time to estimate σ_n is fast.

Table 1. The peak signal to noise ratio (PSNR) of different denoising methods for image Fingerprint. The best results are highlighted in bold font.

Noise Type	Noise Level	Noisy	BivShrink	BM3D	PGBM3D	Proposed
Gaussian (σ_n)	20	20.10	28.56	**28.83**	26.48	**28.83**
	40	16.08	25.05	**25.51**	22.28	**25.51**
	60	12.56	23.17	**23.75**	21.64	**23.75**
	80	10.06	21.93	**22.54**	19.73	**22.54**
	100	8.12	21.01	**21.55**	17.74	**21.55**
Signal Dependant (k_0, k_1)	(10,0.1)	20.26	27.11	**27.39**	25.72	27.16
	(10,0.3)	13.35	21.66	**23.45**	19.56	**23.45**
	(10,0.5)	9.54	18.45	21.44	15.63	**21.84**
	(10,0.7)	6.90	16.20	19.76	12.95	**20.64**
	(10,0.9)	4.88	14.39	17.77	11.38	**18.97**

Table 2. The peak signal to noise ratio (PSNR) of different denoising methods for image House. The best results are highlighted in bold font

Noise Type	Noise Level	Noisy	BivShrink	BM3D	PGBM3D	Proposed
Gaussian (σ_n)	20	22.08	31.77	**33.78**	29.29	**33.78**
	40	16.06	28.62	**30.64**	27.32	**30.64**
	60	12.54	26.83	**28.76**	25.73	**28.76**
	80	10.04	25.58	**27.15**	24.37	**27.15**
	100	8.10	24.61	25.89	23.16	**26.17**
Signal Dependant (k_0, k_1)	(10,0.1)	20.42	30.31	**32.31**	28.97	**32.31**
	(10,0.3)	13.59	23.44	**27.06**	21.32	**27.06**
	(10,0.5)	9.80	19.39	23.97	17.15	**27.13**
	(10,0.7)	7.17	16.58	21.29	14.38	**25.30**
	(10,0.9)	5.16	14.49	18.49	12.37	**23.91**

Table 3. The peak signal to noise ratio (PSNR) of different denoising methods for image Lena. The best results are highlighted in bold font.

Noise Type	Noise Level	Noisy	BivShrink	BM3D	PGBM3D	Proposed
Gaussian (σ_n)	20	22.09	32.30	**33.03**	29.11	**33.03**
	40	16.08	29.20	**29.82**	27.03	**29.82**
	60	12.56	27.37	**28.15**	25.68	**28.15**
	80	10.06	26.05	**26.82**	24.74	**26.82**
	100	8.12	25.10	**25.76**	24.01	**25.76**
Signal Dependant (k_0, k_1)	(10,0.1)	20.92	30.05	**31.70**	28.86	**31.70**
	(10,0.3)	14.26	22.42	26.27	21.36	**28.87**
	(10,0.5)	10.52	18.22	23.43	17.34	**27.10**
	(10,0.7)	7.91	15.38	21.13	14.63	**25.75**
	(10,0.9)	5.91	13,26	18.87	12.57	**24.60**

Table 4. The peak signal to noise ratio (PSNR) of different denoising methods for image Peppers. The best results are highlighted in bold font.

Noise Type	Noise Level	Noisy	BivShrink	BM3D	PGBM3D	Proposed
Gaussian (σ_n)	20	22.08	29.93	**31.27**	28.09	**31.27**
	40	16.06	26.44	**27.64**	25.26	**27.64**
	60	12.54	24.54	**25.74**	23.67	**25.74**
	80	10.04	23.27	**24.37**	22.32	**24.37**
	100	8.10	22.32	**23.31**	20.93	**23.31**
Signal Dependant (k_0, k_1)	(10,0.1)	20.89	28.51	**29.80**	27.78	**29.80**
	(10,0.3)	14.19	21.83	24.35	20.65	**26.40**
	(10,0.5)	10.44	17.77	21.62	16.67	**24.38**
	(10,0.7)	7.83	14.98	19.51	13.92	**22.84**
	(10,0.9)	5.82	12.91	17.45	12.03	**21.66**

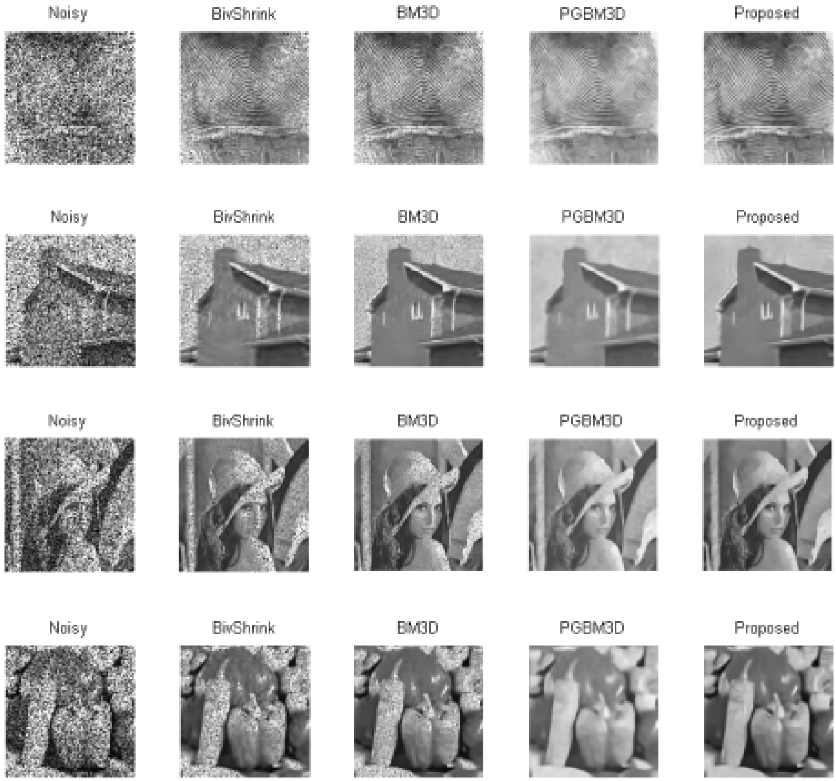

Fig. 1. The noisy images, the denoised images by BivShrink, BM3D, PGBM3D, and the Proposed method for Fingerprint, House, Lena, and Peppers, respectively

4 Conclusions

Reducing noise in digital images corrupted with additive, multiplicative, and mixed noise is a very important topic in image processing. In this paper, we have proposed a new method for reducing the noise in the noisy image. Our method reduces the noise in the residual image and merges this denoised residual image into the previously denoised main image. In this way, more fine features in the image will be retained. Our new denoising method in this paper works well for both the Gaussian white noise and signal-dependent noise. In addition, it nearly always outperforms the BM3D, Poisson-Gaussian BM3D (PGBM3D), and Bivariate shrinking (BivShrink) for signal dependent noise. It achieves similar results as the BM3D for Gaussian white noise.

Future research will be conducted in order to deal with other types of noise in the noisy 1D signals, 2D images, and 3D videos. We may replace the BM3D algorithm with our previous works ([9], [10], [11], [12], [13], [14]) for image denoising. We believe that our proposed method may be applied to multi-spectral or hyper-spectral satellite imagery as well. In addition, we will use other metrics to measure the image visual quality of the denoised images. For instance, we can use such metrics as MSSIM [20], VIF [21], MSE, etc.

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