Images Denoising with Feature Extraction for Patch Matching in Block Matching and 3D Filtering

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Abstract. In this paper, we propose a new method for grey scale image denoising. Our method takes advantage of the fact that the mean of the Gaussian white noise is zero. For every patch in the noisy image, we use a line to divide the image into two regions with equal area, and then take the mean of one of the two regions. We select lines with different slopes in order to extract a number of features. We use these extracted features to match the patches in the noisy image. All other steps in our method are the same as those in the standard BM3D. Our experimental results show that our new method outperforms the standard BM3D for σ_n>120, and they are identical, otherwise.

Keywords: Image denoising, block matching and 3D filtering (BM3D), Gaussian white noise.

1 Introduction

Noise reduction of an image is a very important problem in a number of real-life applications. Gaussian white noise is the most popular topic in the literature. We formulate this kind of noise in image B as [1]:

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

where A is the noise-free image, σ_n is the noise standard deviation, and Z is the Gaussian white noise with N(0,1) distribution.

There are many methods in the literature for reducing this kind of noise. Sendur and Selesnick [1] proposed a bivariate denoising method by employing parent-child relationship in the wavelet domain. Dabov et al. [2] developed the block matching and 3D filtering (BM3D) for image denoising. Chen and Wu [3] investigated the so-called bounded BM3D (BBM3D) method for image denoising. Luisier et al. [4] proposed a SURE-based denoising method for image denoising. Chen and Kegl [6] proposed an

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image denoising method by using complex ridgelets. Chen et al. ([7], [8]) developed two image denoising methods by considering coefficient dependency in the wavelet domain. Cho et al. [9] also proposed several denoising techniques for images. Cho and Bui [10] studied multivariate statistical modeling for image denoising using wavelet transforms. Recently, there are a few new image denoising methods appeared in the literature. Fathi and Naghsh-Nilchi [11] proposed an efficient image denoising method based on a new adaptive wavelet packet thresholding function. Chatterjee and Milanfar [12] studied patch-based near-optimal image denoising. Rajwade et al. [13] worked on image denoising using the higher order singular value decomposition. Motta et al. [14] proposed the iDUDE framework for gray scale image denoising. Miller and Kingsburg [15] studied image denoising using derotated complex wavelet coefficients.

In this paper, we propose a new method for reducing Gaussian white noise in images. Our method is based on block matching and 3D filtering (BM3D) [2], which is the state-of-the-art in image denoising. We use lines with different slopes to divide each patch into two regions and then calculate the means of these regions because we can take advantage of the zero mean of the Gaussian white noise. We use these extracted features to align the image patches. All other steps in our method are identical to those in the BM3D method. Experimental results show that our method outperforms existing denoising methods in heavy noisy environment.

The organization of this paper is as follows. Section 2 proposes a new method for reducing the Gaussian white noise in an image. Section 3 conducts some experiments in order to show the superiority of our new method. Finally, Section 4 concludes the paper and proposes future research directions.

2 Proposed Method

In this section, we propose a new method to reduce the Gaussian white noise in a noisy image. The noise standard deviation can be approximated as [5]:

$$\sigma_n = \frac{median(|y_{1i}|)}{0.6745}, \quad y_{1i} \in \text{subband } HH_1. \tag{2}$$

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

We know that the mean of Gaussian white noise is zero, so we divide each image patch into two regions with equal area and then calculate the mean of one of these two regions. We choose a number of lines with different slopes so that a moderate number of features can be extracted from the image patches. Let $k \in [1, K]$, where K×K is the size of the image patch. We choose the lines passing through the following two points as in Cases 1 and 2:

Case 1: (1,k) and (k,K-k)
Case 2: (k,1) and (K-k,k)

The total number of features for each patch is then *2K+1* whereas the patch size is K^2. It is easy to know that these lines divide the image patches into two regions with equal area. We then take the mean of one of the two regions for each line and use the extracted mean features to match the patches, where the nearest neighbour classifier is utilized. The closest patches should have the smallest distance in these features. All other procedures in our denoising method are the same as those of the BM3D. Figs. 1 and 2 show the noise-free patch with 8×8 and 16×16 pixels, its noisy patch (σ_n =140), the extracted features from both the noise-free and noisy patches, and the difference between the noise-free and noisy features. The horizontal axes of the two lower sub-figures are the feature size, and the vertical axes represent the extracted features (lower-left) and difference of features between the noise-free and noisy patches. It can be seen that our extracted features are very robust to Gaussian white noise.

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

Step 1. Given the noisy grey scale image B, estimate the noise standard deviation σ_n from B according to equation (2).

Step 2. If $\sigma_n \le 120$, then perform BM3D to B as $B_1 = BM3D(B, \sigma_n)$. Set $\tilde{B} = 255 \times B_1$ since BM3D scales the output image to the range of [0,1]. Stop.

Step 3. If $\sigma_n > 120$, then use a number of lines with different slopes to divide each patch into two regions with equal area. Calculate the means of one of the two regions.

Step 4. Use these extracted features to match the patches in the noisy image.

Step 5. Denoise the 3D patches and then put back the denoised patches, just like the standard BM3D. Stop.

The major contribution of this paper is the following. Our proposed method falls back the standard BM3D when the noise level is not high. In addition, it outperforms the BM3D when $\sigma_n > 120$ in terms of PSNR. Furthermore, the feature length of our extracted features from patches is shorter than the patch size. This means that our method should be fast as well. However, the calculation of the mean features from each patch is time consuming. Our experiments show that our new denoising method is a bit slower than the standard BM3D for denoising images.

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 grey scale images: Lena, Boat, and Barbara. We generate the noisy images by using equation (1). Fig. 3 displays these three images, which are frequently used in other denoising papers in the literature. We compared our method with the standard BM3D [2], the bounded BM3D (BBM3D [3]), and the SURELET [4] for image denoising. Tables 1-3 tabulate the peak signal to noise ratio (PSNR) of the BBM3D, SURELET, BM3D and our proposed method in this paper for these three images, respectively. The PSNR is defined as

$$PSNR = 10\log_{10}\left(\frac{M \times N \times 255^2}{\sum_{i,j}(B(i,j) - A(i,j))^2}\right) \quad (3)$$

where $M \times N$ is the number of pixels in the image, and A and B are the noise-free and denoised images. It can be seen that our proposed method is identical to BM3D for noise standard deviation $\sigma_n \leq 120$, and our method outperforms the SURELET, BBM3D, and BM3D methods for nearly all other cases. The only exception is in Table 2, where the SURELET is the best for $\sigma_n=220$ and $\sigma_n=240$. However, the SURELET is only a bit better than our proposed method for these two cases. Figs. 4-6 show the noise-free, noisy ($\sigma_n=220$), and the denoised images by SURELET, BBM3D, BM3D, and the proposed methods for the Lena, Boat, and Barbara images. It can be seen that our denoised images are closer to the noise-free images than images generated by all other three methods in the experiments. The images obtained by BBM3D and BM3D do not have smooth regions as the noise-free image, but our new method does.

Table 1. The PSNR of different denoising methods for image Lena with Gaussian white noise. The best results are highlighted in bold font.

σ_N	Noisy	SURELET	BBM3D	BM3D	Proposed
20	22.10	31.36	**33.03**	**33.03**	**33.03**
40	16.08	28.29	**29.82**	**29.82**	**29.82**
60	12.56	26.59	26.63	**28.15**	**28.15**
80	10.06	25.45	24.97	**26.82**	**26.82**
100	8.12	24.59	23.67	**25.76**	**25.76**
120	6.53	23.90	22.60	**24.89**	**24.89**
140	5.20	23.32	21.59	23.62	**24.10**
160	4.04	22.81	20.65	21.95	**23.47**
180	3.01	22.37	19.77	20.86	**22.91**
200	2.10	21.96	18.88	19.98	**22.37**
220	1.27	21.59	17.99	19.15	**21.87**
240	0.51	21.25	17.09	18.45	**21.41**

Table 2. The PSNR of different denoising methods for image Boat with Gaussian white noise. The best results are highlighted in bold font.

σ_N	Noisy	SURELET	BBM3D	BM3D	Proposed
20	22.10	29.40	30.76	**30.79**	**30.79**
40	16.08	26.39	**27.63**	**27.63**	**27.63**
60	12.56	24.80	25.03	**25.90**	**25.90**
80	10.06	23.79	23.63	**24.74**	**24.74**
100	8.12	23.06	22.48	**23.88**	**23.88**
120	6.53	22.49	21.53	**23.16**	**23.16**
140	5.20	22.03	20.73	22.21	**22.43**
160	4.04	21.63	19.96	20.92	**21.93**
180	3.01	21.29	19.23	20.12	**21.49**
200	2.10	20.99	18.56	19.46	**21.06**
220	1.27	**20.71**	17.91	18.81	20.67
240	0.51	**20.46**	17.21	18.22	20.30

Table 3. The PSNR of different denoising methods for image Barbara with Gaussian white noise. The best results are highlighted in bold font.

σ_N	NOISY	SURELET	BBM3D	BM3D	PROPOSED
20	22.10	27.81	**31.73**	**31.73**	**31.73**
40	16.08	24.53	**28.00**	**28.00**	**28.00**
60	12.56	23.14	23.58	**26.33**	**26.33**
80	10.06	22.35	22.36	**24.84**	**24.84**
100	8.12	21.79	21.46	**23.66**	**23.66**
120	6.53	21.32	20.70	**22.69**	**22.69**
140	5.20	20.93	19.97	21.31	**21.64**
160	4.04	20.58	19.29	20.14	**21.20**
180	3.01	20.28	18.62	19.45	**20.79**
200	2.10	20.00	17.91	18.78	**20.44**
220	1.27	19.74	17.20	18.16	**20.09**
240	0.51	19.51	16.51	17.63	**19.77**

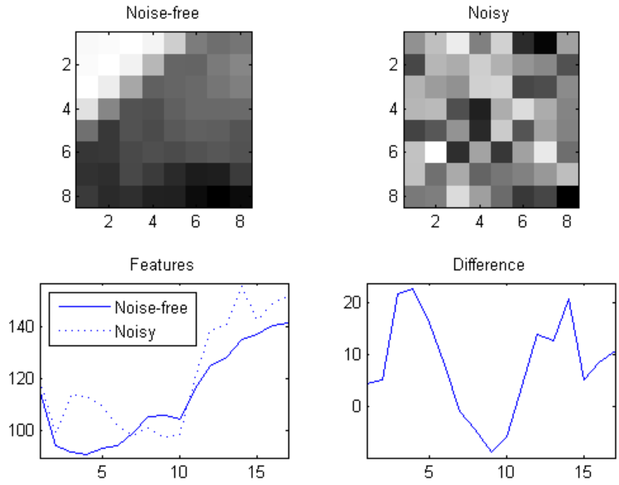

Fig. 1. The noise-free patch with 8×8 pixels, its noisy patch (σ_n =140), the extracted features from both patches, and the difference between the noise-free and noisy features. The horizontal axes of the two lower sub-figures are the feature size, and the vertical axes represent the extracted features (lower-left) and difference of features between the noise-free and noisy patches. It can be seen that our extracted features are robust to Gaussian white noise.

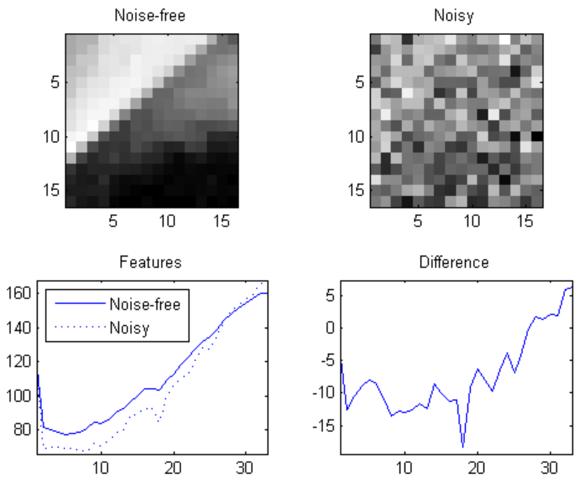

Fig. 2. The noise-free patch with 16×16 pixels, its noisy patch (σ_n =140), the extracted features from both patches, and the difference between the noise-free and noisy features. The horizontal axes of the two lower sub-figures are the feature size, and the vertical axes represent the extracted features (lower-left) and difference of features between the noise-free and noisy patches. It can be seen that our extracted features are robust to Gaussian white noise.

Fig. 3. The three images used in our experiments: Lena (left), Boat (middle), and Barbara (right)

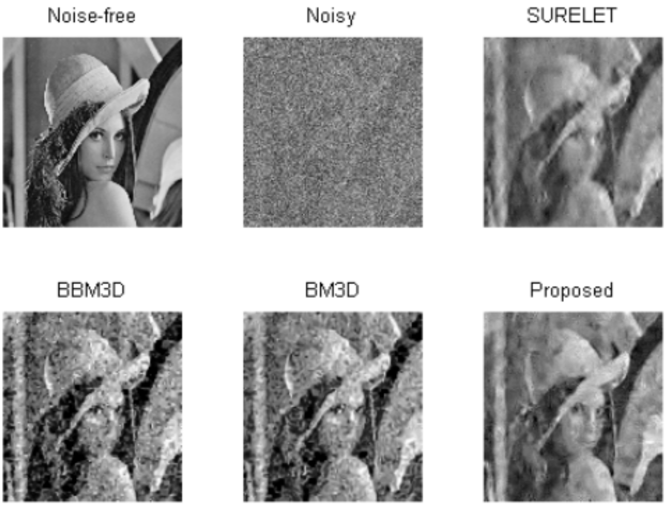

Fig. 4. The noise-free, noisy (σ_n=220), and the denoised images by SURELET, BBM3D, BM3D, and the proposed methods for the Lena image

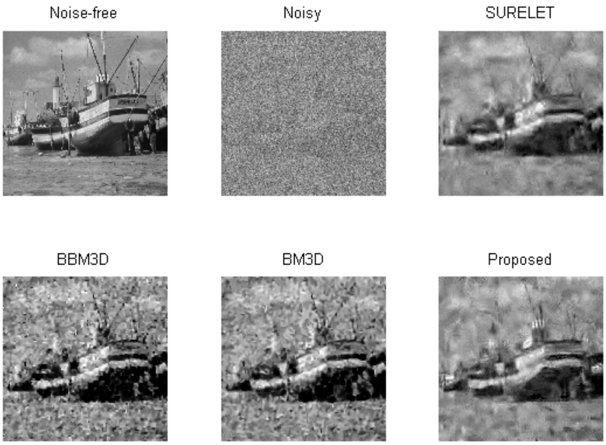

Fig. 5. The noise-free, noisy (σ_n=220), and the denoised images by SURELET, BBM3D, BM3D, and the proposed methods for the Boat image

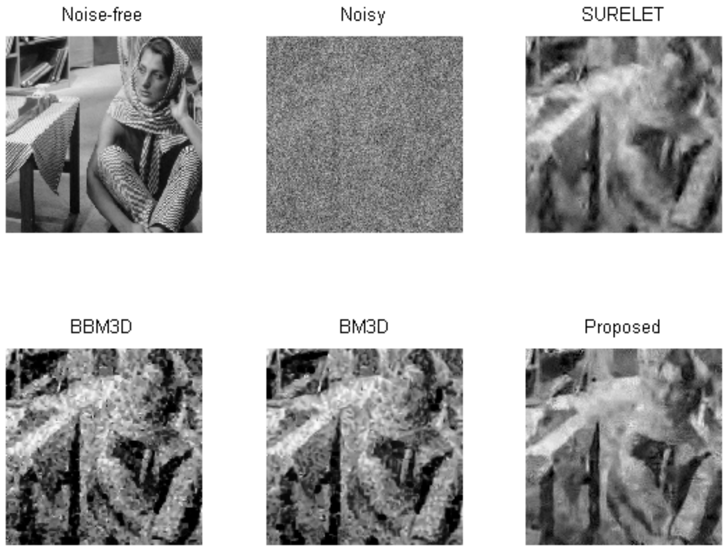

Fig. 6. The noise-free, noisy (σ_n=220), and the denoised images by SURELET, BBM3D, BM3D, and the proposed methods for the Barbara image

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.

4 Conclusions and Future Works

In this paper, we have proposed a new method for reducing the Gaussian white noise by extracting features from each patch and align the patches by using these features. The closest patches should have the smallest distance in these features. All other steps in our new method are identical to the BM3D. Our experiments show that our new method outperforms the standard BM3D under heavy noise environment and it is identical to the BM3D method for other noisy conditions. Our new method is nearly always better than the BBM3D and SURELET methods for image denoising except two cases in Table 2, where the SURELET method is the best among all three compared methods.

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 believe that our proposed method in this paper may also be applied to multi-spectral or hyper-spectral satellite imagery as well. Furthermore, we would like to align the image patches by affine transformation so that better denoising results can be obtained.

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