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Image Denoising by Fourier block processing and Wiener filtering

Naveen S.^a, Aiswarya V.A.^{a*}

^a LBS Institute of Technology for women, Poojappura, Thiruvananthapuram-695012, India

^b LBS Institute of Technology for women, Poojappura, Thiruvananthapuram-695012, India

Abstract

The purpose of image denoising is to get a clear version of a noisy image. Although the current denoising methods produce acceptable results; they suffer from certain visible artifacts. We propose a method for image denoising, which can be implemented in both spatial and spectral domains. We offer an image denoising method based on block processing and wiener filtering. The experimental results demonstrate that this algorithm achieves good performance in terms of both peak-signal to noise ratio (PSNR) and visual quality.

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1. Introduction

There are plenty of denoising methods, from various disciplines such as statistics, linear and non-linear filtering, spectral and multiresolution analysis. The images may get contaminated through analog process during transport over analog media. The most common assumption is that the noise is Additive White Gaussian Noise (AWGN) and also the noise is stationary and uncorrelated among pixels. The current method used to denoise an image is Block Matching with 3D filtering (BM3D) [1]. Natural image denoising [2] shows that, BM3D is close to the theoretical limit of denoising, but synthetic and highly correlated images still need improvement. Dual Domain Image Denoising (DDID) proposed by Knaus and Zwicker, demonstrated that simple algorithm can achieve high quality results [3]. We propose a method by which the noisy image is denoised by filtering both spatial and spectral domain.

* Corresponding author.

E-mail address: aiswaryava7142@gmail.com

Here, we use bilateral filter in spatial domain and Block Discrete Fourier Transform (Block DFT) in frequency domain. Wiener filter is used to shrink the transform coefficients. Our method works well for colour images also. For colour images, block DFT is applied on each colour channel. This method produces high quality results in terms of peak-signal to noise ratio (PSNR) and visual quality. The paper is organized as follows. Review the existing methods for image denoising is given in section 2. Section 3 explains the proposed image denoising algorithm. Section 4 deals with the results and discussion followed by conclusion.

2. Related Works

The state-of-the-art denoising method is held by Block Matching with 3D filtering (BM3D) [1],[12]. It is based on an enhanced sparse representation in transform domain. The enhancement of sparsity is achieved by stacking the collected similar patches on top of each other. 3D wavelet shrinkage is used to denoise these 3D stacks. BM3D-SAPCA [4] is an improved version of BM3D modifies the patches by polygonal shape masks and performs a PCA to find sparse representation of patches. Non-local Bayes (NLB) [6] uses matrix inversion for solving the most likely patches. For colour images NLB is better than BM3D. Dual Domain Image Denoising (DDID) [3] operates in spatial domain and transform domain. Bilateral filter and non-local means filter are used in spatial domain to define filter kernel. They preserve features like edge, but face difficulties in preserving low contrast details. Wavelet thresholding and shrinkage methods operate in transform domain and excel in preserving textures, but they suffer from artifacts near edges. Moreover DDID is an iterated and guided method which produces results competitive with BM3D. Progressive Image denoising (PID) [4] is a denoising method derived from DDID. PID differentiates itself by allowing iteration using arbitrary fine time steps and by avoiding distinction between noisy and guide images. PID also inspired by deterministic annealing (DA) [5] and simulated annealing (SA) [10]. DA and SA are suited for complex optimization problems with priori unknown global energy.

Our method is inspired from Dual Domain Image Denoising (DDID) [3] and Progressive Image Denoising (PID) [4]. We perform filtering operation both in spatial and transform domains. In spatial domain, bilateral kernel is used. In frequency domain the filtering operation is enhanced by block DFT and Wiener filtering. Our method works well for colour images also. In the case of colour images, instead of block DFT, block DCT can be applied.

3. Denoising by Fourier block processing and Wiener filtering

Our denoising method is implemented using a simple filtering scheme. The task is to decompose the noisy signal 'y' into its original signal 'x' and noise instance 'n' as

$$y = x + n. \quad (1)$$

The noise is 'n' assumed to be Gaussian and has variance $\sigma^2 = \text{Var}[n]$. We separate the input noisy image into two layers, high contrast layer and low contrast layer. Bilateral filter is used to denoise the high contrast layer in spatial domain. The low contrast layer of the residual image is denoised by shrinking transform coefficients using Wiener filtering. The original image is the sum of these two denoised layers.

$$x = \tilde{s} + \tilde{S}. \quad (2)$$

Bilateral filter protects large amplitudes and wavelet shrinking discards smaller amplitudes and thus denoising operates between these two amplitudes.

3.1. Spatial Domain processing

We consider a window N_p of radius r having adjacent pixels p and q . Bilateral filter [6], [9], [11] uses a guide image g to denoise the noisy image y . Here, a bilateral filter is used to denoise both guide and noisy images to get high contrast values as

$$\widetilde{g}_p = \frac{\sum_{q \in N_p} k_{p,q} g_q}{\sum_{q \in N_p} k_{p,q}} \quad (3)$$

$$\widetilde{s}_p = \frac{\sum_{q \in N_p} k_{p,q} y_q}{\sum_{q \in N_p} k_{p,q}} \quad (4)$$

where the bilateral kernel is

$$k_{p,q} = e^{-\frac{|p-q|^2}{2\sigma_s^2}} e^{-\frac{(g_p - g_q)^2}{\gamma_r \sigma^2}} \quad (5)$$

The guide image is a noiseless image of the corresponding noisy image. The parameters σ_s and γ_r are shape and range kernel respectively. The low contrast value can be found out by subtracting \widetilde{g}_p and \widetilde{s}_p from g_p and s_p followed by multiplication with range kernel.

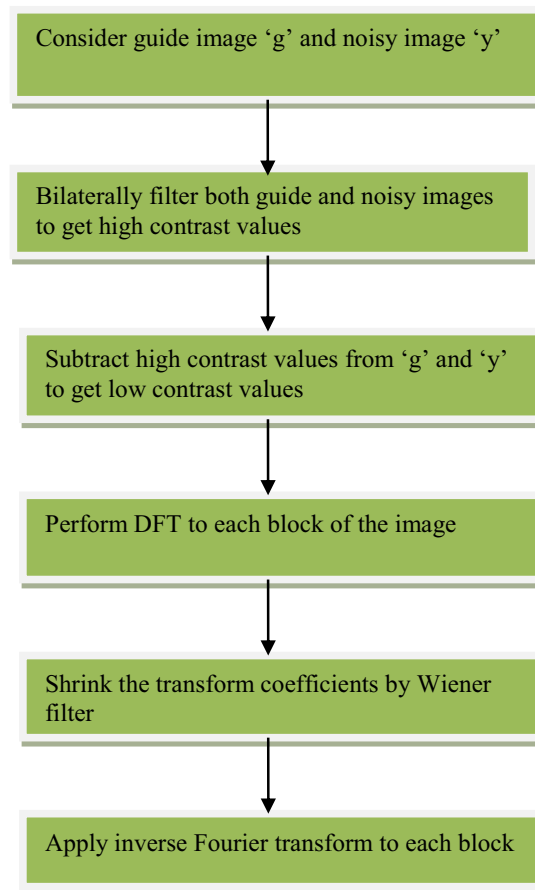


Fig.1. Flow chart of the proposed denoising algorithm

3.2. Spectral Domain processing

Block wise Discrete Fourier Transform is applied on the low contrast signals in the frequency domain, yielding the Fourier coefficients $G_{p,f}$ and $S_{p,f}$ for frequency f . When working with large images, normal image processing techniques can sometimes break down. The images can either be too large to load into memory, or else can be loaded into memory but then be too large to process. To avoid these problems, we can use block processing.

In block processing with DFT, divide the input image into blocks of specified size, and process them using the function DFT handle one block at a time, and then assembles the result into the output. Each block contains M rows and N columns. Noisy Fourier coefficients of $S_{p,r}$ is shrunk by means of Wiener filtering [13]. It filters the image using pixelwise adaptive filtering using neighbourhoods of size M and N to estimate the local image mean and standard deviation. Wiener filter is the MSE-optimal stationary linear filter for images degraded by additive noise and blurring. Calculation of the Wiener filter requires the assumption that the signal and noise processes are second order stationary. The image spectrum is estimated by taking the Discrete Fourier Transform of the image and the Wiener filter. A low contrast value \tilde{S}_p over the frequency domain F_p is obtained by taking inverse DFT of the shrunk coefficients [3] for one block at a time and assembles these into output.

3.3. Colour Images

Colour images are made up of 3 colour channels (RGB) whereas gray scale images contain only a single colour channel. The colour image is split up into 3 channels, one for each of the Red, Green and blue components.

Each of these can be processed with block DFT independently. Instead of block DFT, 3-point Discrete Cosine Transform (DCT) can also be used by considering each block at a time. Since DCT is a unitary transformation, the noise variances remain constant and uncorrelated. The PSNR of the resulting images of these two methods are discussed in the upcoming sections.

4. Results and discussions

In this section we present and discuss the experimental results obtained by the algorithm. Figure 1 represents the flow chart of the proposed method. Window radius is $r=3$ and reference spatial sigma $\sigma_s=7$. The range scale $\gamma_r=8.7$ and for the spatial scale $\gamma_s=0.4$. We consider gray scale image of size 256×256 . The image is added with noise having standard deviation $\sigma=25$ and zero mean. For block processing the required function (DFT or IDFT) [15] is applied on each specified size of block on the image. The size of the block may $8 \times 8, 16 \times 16, 48 \times 48, 64 \times 64, 128 \times 128$. From the figure 2, it is clear that the optimum block size is 8×8 .

Table 1: PSNR (dB) comparison of gray scale images

Gray scale $\sigma = 10$	Barbara	Cameraman	Montage	Lena
Proposed method	34.73	34.21	37.53	35.87
PID	34.55	34.14	37.43	35.81
DDID	34.67	34.05	37.51	35.81
NLB	34.82	34.43	37.28	35.78
BM3D-SAPCA	35.10	34.59	37.85	36.07
$\sigma = 25$				
Proposed method	30.83	29.79	32.73	32.20
PID	30.56	29.68	32.76	32.12
DDID	30.80	29.47	32.61	32.14
NLB	30.24	29.44	31.95	31.80
BM3D-SAPCA	31.00	29.81	32.97	32.23
$\sigma = 40$				
Proposed method	28.59	28.01	30.28	30.17
PID	28.38	27.60	30.25	30.14
DDID	28.51	27.32	29.82	30.07
NLB	28.05	27.13	29.10	29.83
BM3D-SAPCA	28.68	27.57	30.02	30.10

The proposed method is suitable for colour and gray scale images. This method produces sharper edges and clear tips. While comparing with other methods such as PID and DDID, our method shows better results.

Basically, the 2D FFT gives us an image of the intensity of low frequency to high frequency information. The centre of the image is low frequency information (such as flat surface, skin, walls) and the corners are high frequency information (edges, grainy noise, and intricate patterns). If we are using Matlab, we have to shift the 2D FFT to put the low frequency information in the centre of the image. It is also good idea to normalize the 2D FFT, so we can see the details better. The 2D DCT is very similar to 2D FFT; it also gives us an image of the intensity of low frequency to high frequency information, but the low frequency information in the top left corner and high frequency information in the bottom right corner. Here, the 2D DCT [14] is used on the blocks of a colour image (8×8 blocks). This gives frequency information that is still related to its location in the spatial range.



Fig.2. Comparison of denoising of images with different block size.(a) input noisy image with $\sigma=25$; (b) 8×8 block (32.20 dB);(c) 16×16 block (32.18 dB); (d) 48×48 block (32.17dB); (e) 64×64 block (32.15 dB); (f) 128×128 block (32.14 dB)

Our method works well for natural images also. The denoised images have smoother edges. Our method excels in denoising in colour images (Fig 3). Since colour channels are highly correlated, signals are better separated from noise. In the case of colour images, instead of block DFT, block DCT is applied.

Table 1 represents PSNR comparison of gray scale images with $\sigma = 10$ and $\sigma = 25$. Numerically the proposed method and PID exhibit comparable denoising qualities. Colour image is made up of 3 colour channels such as red, Green and blue. The denoising algorithm is applied on each channel separately. Here we are denoised the images using Block DFT and Block DCT. The PSNR values of the resulting images are shown in the Table 2. These values show that Block DFT is better than Block DCT.



Fig. 3 . Comparison of DDID, PID and proposed method (a) Noisy image ($\sigma = 25$); (b) DDID (30.80 dB); PID (30.56 dB); (d) Proposed method (30.83 dB)

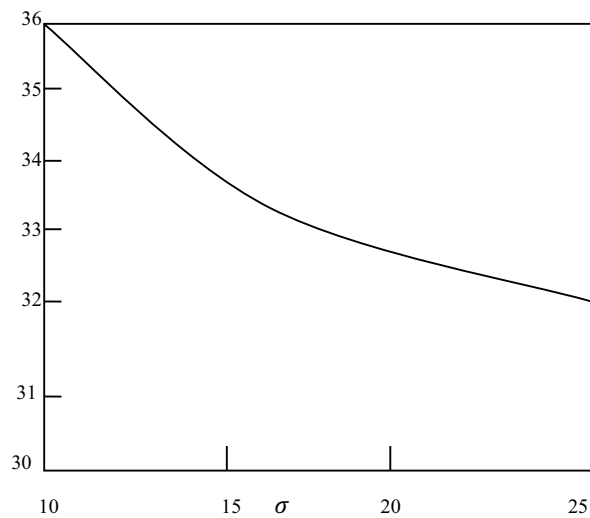


Fig.4. PSNR values of gray scale image (Lena)

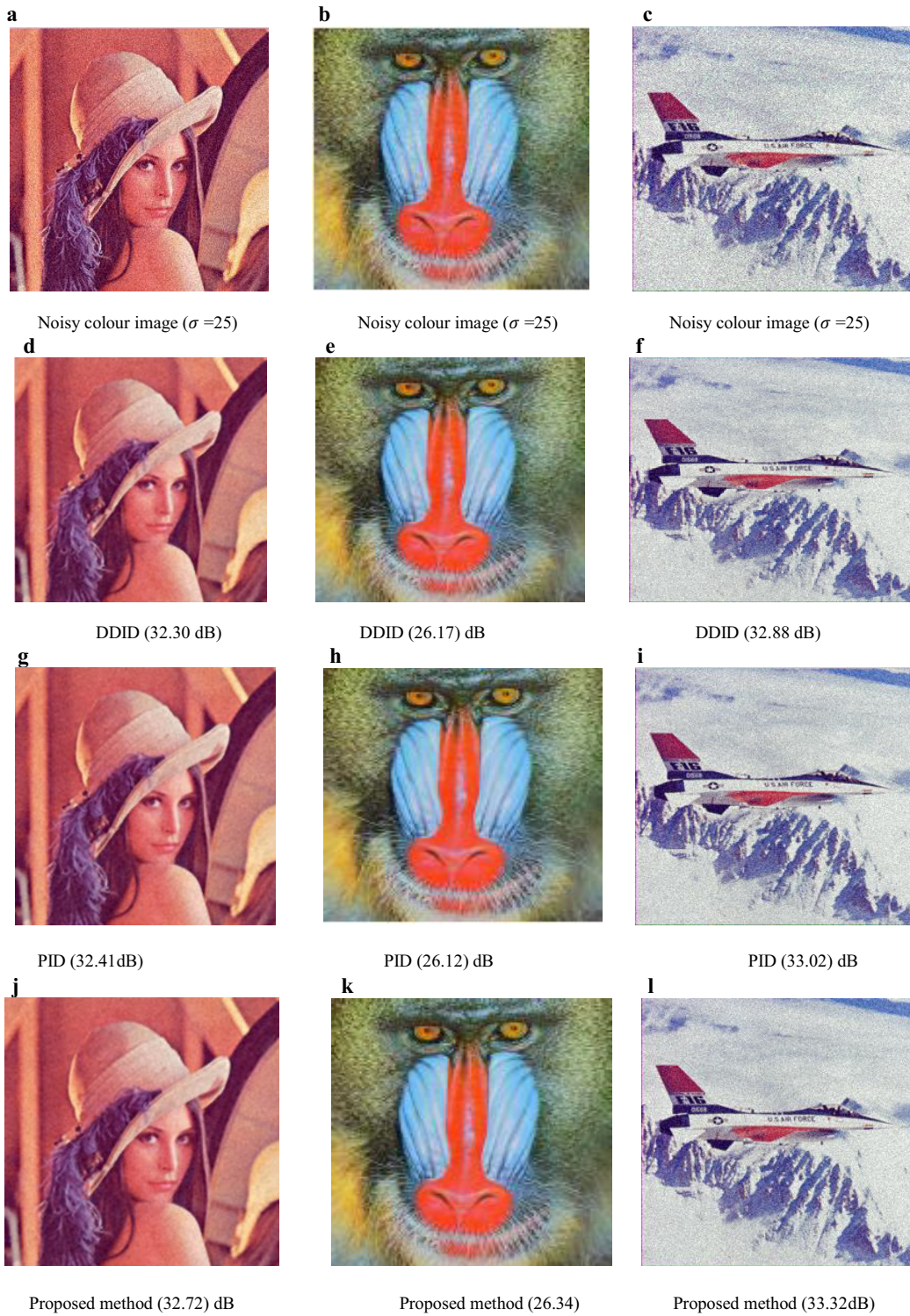


Fig.5. Denoising of colour images

Table 2: PSNR comparison of colour images

Colour image $\sigma = 25$	House	Lena	Pepper	Tiffany
Proposed method				
(a) Block DFT	32.95	32.72	31.50	32.59
(b) Block DCT	32.93	32.51	31.41	31.57
PID	32.90	32.41	31.36	32.61
DDID	32.69	32.30	31.25	32.49
NLB	32.69	32.27	31.20	32.47
$\sigma = 50$				
Proposed method				
(a) Block DFT	30.71	30.26	30.01	29.95
(b) Block DCT	30.64	30.17	29.98	29.52
PID	30.54	30.07	29.34	30.12
NLB	30.38	29.85	29.09	29.61

6. Conclusion

We have presented a simple denoising method which produces high quality results. Here a guide image is used to denoise the noisy image. Denoising takes place in two domains, spatial domain and frequency domain. A bilateral filter is used in spatial domain. The image is processed by block DFT, block IDFT and Wiener filtering in frequency domain. We have applied denoising algorithm for various block sizes such as 8×8 , 16×16 , 48×48 , 64×64 and 128×128 . After comparing the PSNR values, the optimum block size is determined as 8×8 . The proposed method works well for colour images also where block DCT is used. Our denoising strategy possesses good PSNR values and high visual quality.

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