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Gaussian Noise Removal in an Image using Fast Guided Filter and its Method Noise Thresholding

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Abstract
A new denoising algorithm using Fast Guided Filter and Discrete Wavelet Transform is proposed to remove Gaussian noise in an image. The Fast Guided Filter removes some part of the details in addition to noise. These details are estimated accurately and combined with the filtered image to get back the final denoised image. The proposed algorithm is compared with other existing filtering techniques such as Wiener filter, Non Local means filter and bilateral filter and it is observed that the performance of this algorithm is superior compared to the above mentioned Gaussian noise removal techniques. The resultant image obtained from this method is very good both from subjective and objective point of view. This algorithm has less computational complexity and preserves edges and other detail information in an image.

Keywords: Fast Guided Filter, Method Noise, Wavelet Thresholding.

Introduction

An image is corrupted by noise during the acquisition and transmission [1]. Unless the noise is removed, it will affect the accuracy of other high level image processing techniques such as segmentation, feature extraction, object recognition and detection etc. [2]. Hence noise removal becomes a vital step in image processing and also it is part of other important image processing techniques [3]. During the acquisition of an image, noise having Gaussian distribution is encountered frequently. Thermal motion of electrons causes the photoelectric sensors to introduce Gaussian noise in an image during the acquisition process [4]. The electromagnetic interferences may also introduce Gaussian noise during the transmission. High temperature and/or poor illumination will also induce Gaussian noise in an image [5]. Gaussian noise is evenly distributed over the image. Hence each pixel in the noisy image is the sum of original pixel value and zero mean Gaussian distribution noise [6].

Lots of work has been carried out to remove the Gaussian noise in images. But, still there is a scope for improvement and fine tuning of existing techniques. Filtering the Gaussian noise in spatial domain creates computation problems as it involves convolution between noisy image and filter kernel. Since convolution is mathematically tedious process, frequency domain methods were developed. However, the optimal frequency domain filter called Wiener filter not only suppresses the noise but also removes fine details (high frequency content) of the image such as points, edges and lines. Hence the resultant image will become more smoothened or more blurred. As Fourier basis analyses the image globally, it fails to take care of local features. To tackle this problem, transform with basis which takes local feature into account, known as wavelet transform was developed for denoising. In wavelet domain, the details of the image are embedded into few coefficients, whereas the noise is distributed across all coefficients. The coefficients of noise are discarded whereas the coefficients of details are retained by comparing with the proper threshold value. D. Donoho and I. Johnstone proposed wavelet based thresholding [7]. However, this method results in more smoothing of fine details. In [8,9] total variation based image denoising was analysed and its relation with soft wavelet shrinkage was also studied in detail. Translational Invariant(TI) multiwavelet denoising scheme was proposed by Bui and Chen [10] that gives better results than the TI single wavelet denoising. While conventional spatial domain filters perform averaging in a neighbourhood of the pixel of interest, new type of filters called Non Local Means(NLM) filters were developed which perform filtering within non local domain which has similar neighbourhood besides filtering within the local neighbourhood [11]**.** If the noise density increases, the effectiveness of non local means filter is degraded substantially and the filtered image becomes more blurred and its details are lost. The efficiency is low when pixelwise matching is carried out in NLM [12]. LPG-PCA and BM3D are recent non-local methods which are iterative. They produce very good results [13,14]. Bilateral filter based removal of Gaussian noise in images gained popularity later as it performs spatial averaging besides taking gray level similarities of the neighboring pixels into account during the filtering [15]. But when it comes to filtering near the edges it fails to perform up to the mark. In addition to this, bilateral filtered images suffer from gradient reversal artifacts. This will degrade the quality of reconstructed image. To overcome these drawbacks, bilateral filter is combined with its method noise thresholding to remove Gaussian noise [16]. However, the selection of filtering parameters is a complicated process in bilateral filter. To overcome these problems, a new Gaussian denoising algorithm is proposed using the combination of Fast Guided filter and its method noise thresholding using wavelet transform

This paper is organized as follows: In section II, Fast Guided Filter is briefly reviewed. In section III, Noise removal based on Fast Guided Filter and its method noise thresholding is proposed. In section IV, results and performance of the proposed algorithm are discussed. Sections V concludes the work.

Fast Guided Filter

Fast Guided Filter preserves the edges by using the content of the guidance image. The guidance image can be the image itself or different depending on the application [17]. The filtered image becomes more structured and less smoothed than the input image. In this filtering algorithm, the input image and the guidance image are sub sampled and the local linear coefficients are calculated. Then these coefficients are up sampled and adopted on the guidance image to produce the output. The filtered image is the local linear transformation of guidance image. The output has edges provided if guidance image has edges. As filtering is independent of intensity range and window size, the computational efficiency of Fast Guided Filter is far better than that of the bilateral filter [18].

Let I, G and Y denote input image, guidance image and output image respectively. It is assumed that the linear transform of G is F in a square window W_x centered at the pixel "x" with radius "r"

$$Y_i = a_x + G_i b_x \qquad \forall i \in W_X \qquad (1)$$

Where "i" is the pixel index and "x" is the index of the window; "a_x" and "b_x" are coefficients of linearity and constant in W_x. To determine these linear coefficients some constraints are required from the input image and their values are given by,

$$a_x = \frac{1}{W} \frac{\sum_{i \in W_x} G_i I_i - \mu_x \overline{P}_X}{\sigma_x^2 + \varepsilon} \qquad (2)$$

$$b_x = \overline{P}_x - a_x \mu_x \qquad (3)$$

Where $\overline{P}_x = \frac{1}{W} \sum_{i \in W_x} P_x$

Where μ_x, σ_x are mean and variance of guidance image in the window ε is a regularisation parameter which controls degree of smoothness.

The output of the filter is given as

$$Y_i = \bar{a}_i G_i + \bar{b}_i \tag{4}$$

Where a_i and b_i are average coefficient value of windows overlapping "i"

The output is modeled as

$$Y_i = I_i - n_i \tag{5}$$

Where "n_i" is the noise

Fast Guided Filter and Its Method Noise Thresholding

The block diagram of the proposed algorithm is shown in Fig.1. The difference between the original image I and the denoised image I_D is known as method noise. It is given by

$$MN = I - I_D \tag{6}$$

The image is denoised by fast guided filter and it has very good visual quality. The filter is easy to implement and has high speed. The details in the images are preserved very well. The filter is powerful to denoise an image. In order to identity the noise removed by the Fast Guided Filter, the definition of method noise is refined as the difference between the noisy image I_N and the filtered image which is given by

$$MN = I_N - I_D \tag{7}$$

Where I_N is the noisy image. It is obtained by degrading the original image by Additive White Gaussian Noise (AWGN)

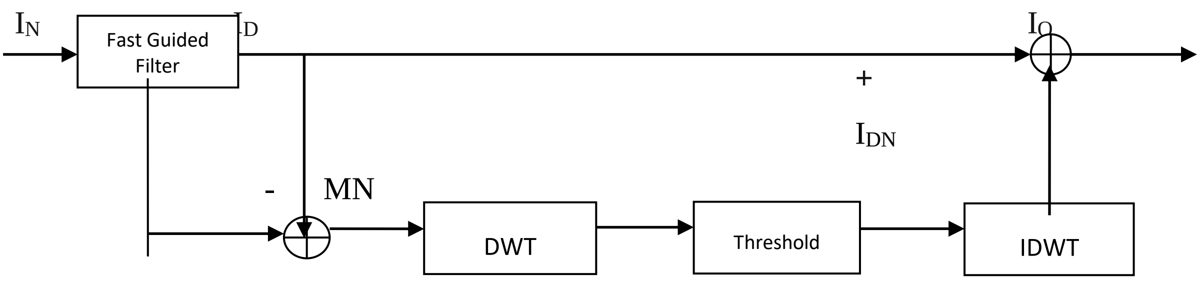


Fig. 1: Block diagram of the proposed algorithm

The method noise comprises both high frequency component of the image and noise as the Fast Guide Filter removes the noise besides the details of the image. Therefore, method noise "MN" can be expressed as the sum of fine details "FD" and Additive White Gaussian Noise "AWGN"

$$MN = FD + AWGN \tag{8}$$

Now the objective is to estimate fine details of the image and it has to be added with the output of the Fast Guide Filter to obtain the denoised image with more information. Decomposing equation [8] by using wavelet transform yields noisy coefficients "NC" which arises due to method noise, the coefficients of details "DC" and Gaussian noise "WN" which is independent of the image and is written as

$$NC=DC+WN \qquad (9)$$

The coefficient of details DC is estimated from noisy coefficients NC in such a way that it minimizes mean square error by thresholding those with appropriate threshold value in the wavelet domain. This ensures that all the features of the original image are preserved in the resultant denoised image. This estimated detail image is added with the filtered image to get the denoised image whose quality is superior compared to the denoised image obtained from Fast Guided filter

Wavelet Thresholding is a nonlinear technique in which the wavelet coefficients are compared with threshold value 'T'. If the magnitude of the coefficient is smaller than threshold value they will be discarded else they will be retained or changed. Usually wavelet coefficients with small absolute value will carry noise information whereas the large wavelet coefficients are dominated by the image.

Thus, the coefficients with noise contents are set to zero and the image is reconstructed with very low noise by applying inverse DWT on the rest of the coefficients. If T is small, it will leave some noisy coefficients intact, on the other hand large T sets many coefficients to zero. Hence the recovered image will become more smoothed and blurred. Hence choosing the threshold value "T" plays a crucial role in denoising

Though many thresholding techniques are available in literatures, BayesShrink is used in this work as its performance is better compared to that of SureShrink in terms of MSE. The reconstructed image appears visually pleasing and smoother. In BayesShrink thresholding carries out soft thresholding and threshold is computed at each sub band level in the wavelet decomposition. This makes the thresholding is sub band dependent. In each sub band Generalized Gaussian Distribution is assumed for the wavelet coefficients. It aims to find T which tries to minimize the Bayesian risk. The threshold value in BayesShrink is given by

$$T_B = \frac{\sigma_n^2}{\sigma_W^2} \qquad (9)$$

Where σ_n^2 is the variance of noise which is estimated by the median estimator [19] from the first decomposition level HH1 and is given by

$$\sigma = \frac{Median(|HH1|)}{0.6745} \qquad (10)$$

and σ_W^2 is the variance of the wavelet coefficients in the same sub band in which noise is estimated.

Proposed Algorithm

Input image =I(x, y)

Noisy image N(x, y) =I(x, y) +n(x, y)

Guidance image =G(x, y)

Enter the values of ε

Enter the value of r

Calculate the mean and variance of G(x, y)

Compute the mean of I(x, y)

Compute the mean of I(x, y)*G(x, y)

Calculate the linear coefficients "a" and" b"

a =(cross [I(x, y) G(x, y)] – mean (G).*mean (I))./(var (G) + ε)

b = mean (I) - a. * mean (G)

Compute the mean of a and b

Output image from Fast Guided Filter Y = mean (a). * G + mean (b)

Method Noise MN=N(x, y)-F(x, y)

Find the DWT of MN

Noisy Coefficients=Coefficients of details+ White Noise

Estimate the threshold using Bayesian shrinkage $T_B = \sigma_n^2 / \sigma_W^2$

Apply soft thresholding on decomposed coefficients and get the estimate of detail coefficients

Perform IDWT

Denoised Image =F(x, y) +Estimate of detail coefficients

Results

To analyse the performance of the proposed noise removal technique, a set of gray scale test images have been taken. The proposed algorithm was tested on those images. The results of the denoising capability of the proposed algorithm in terms of PSNR were compared with other existing noise removal techniques and are presented in table 1 for low and high noise density conditions. Though the performance of conventional filters such as Gaussian filter and Wiener filter were good, their performance was not up to the expected level with respect to noise removal capability. Standard DWT using db4 wavelet with soft thresholding provided high PSNR value compared to conventional filter but its performance degraded when noise density was increased

The PSNR value obtained from the bilateral filter was very good compared to other filtering algorithm since it not only takes pixel location but also considers intensity difference between the pixels. However, the PSNR value of the bilateral filter was less than that of the Improved NLM(INLM) algorithm. Since the computational complexity is more for INLM it is not preferred for real time applications. Bilateral filter based method noise thresholding provided very good PSNR compared to purely bilateral filter based algorithm, since this method not only removes the noisy information but also estimates the details and add it back to the original image

It is evident from the table 1 that the noise removal capability of Fast Guided Filter and its method noise thresholding with regularization parameter of 0.01 and window size of 3 was high. It outperformed all other algorithms as the lost details are reconstructed by using wavelet shrinkage and added back to the denoised image again. So, most of the noise was removed and the details also kept intact. Hence signal power remained high and noise power got reduced which resulted in high PSNR.

Table 1
Comparison of PSNR Values of the Proposed Algorithm with other Existing Methods

	Cameraman Image				**Lena Image**			
Filters	**σ= 10**	**20**	**30**	**40**	**σ= 10**	**20**	**30**	**40**
Gaussian Filter	22.98	22.82	22.56	22.19	30.54	25.60	22.37	20.12
Wiener Filter	26.26	24.91	23.51	22.28	29.64	27.69	26.03	24.64
DWT	31.26	27.16	25.33	23.69	36.58	31.45	28.48	26.37
INLM	33.55	29.43	27.68	26.49	33.26	29.96	28.04	26.70
LPG-PCA	33.92	29.98	27.83	26.62	33.54	30.01	27.76	26.54
Bilateral Filter	29.50	25.91	24.13	23.05	26.90	24.17	23.21	21.29
Bilateral Filter+Method Noise	31.16	27.51	25.22	23.64	31.40	27.54	25.72	24.42
BM3D	34.39	30.72	28.64	27.68	33.91	30.24	28.29	27.26
Proposed Method	39.61	39.04	38.10	36.17	38.90	38.54	37.81	36.79

Table 2 shows the comparison of the proposed algorithm with other denoising algorithms with respect to Structural Similarity Index (SSIM). Since SSIM measures the similarity between two images, it is obvious from the results in table 2 that there is good degree of similarity between the denoised image and the original image in the proposed algorithm. This indicates the superiority of the proposed algorithm in terms of human visual perception. Though other methods such as INLM, BM3D filtering offer very good SSIM, their PSNR is less compared to the proposed algorithm. It is obvious that Gaussian filter and Wiener filter have very less SSIM since they introduce blurring effect. Hence the similarity between the original image and denoised image becomes less. When the noise density increases the similarity is reduced drastically as there will be more blurring effect in these filters. DWT offers very low SSIM value since it loses some details of the image during the thresholding operation. The denoised image of bilateral filter and bilateral filter with method noise shows fair amount of similarity with the original image.

Table 2
Comparison of SSIM Values of the Proposed Algorithm with Other Existing Methods

	Cameraman Image				**Lena Image**			
Filters	**σ= 10**	**20**	**30**	**40**	**σ= 10**	**20**	**30**	**40**
Gaussian Filter	0.7672	0.5413	0.4133	0.3292	0.8109	0.5891	0.4484	0.3582
Wiener Filter	0.8170	0.7611	0.6924	0.6059	0.8249	0.7733	0.7102	0.6373
DWT	0.6319	0.4620	0.3607	0.2844	0.7882	0.5987	0.4708	0.4657
INLM	0.9270	0.8527	0.8035	0.7703	0.9093	0.8510	0.8006	0.7588
LPG-PCA	0.9364	0.8791	0.8269	0.7925	0.9261	0.8583	0.7989	0.7113
Bilateral Filter	0.8166	0.7253	0.6593	0.6110	0.7707	0.6747	0.6298	0.9413
Bilateral Filter +Method Noise	0.9107	0.8436	0.7899	0.7586	0.8897	0.8379	0.7975	0.7324

BM3D	0.9099	0.8993	0.8634	0.8241	0.9274	0.8691	0.8224	0.7861
Proposed Method	0.9201	0.8621	0.7992	0.7731	0.9083	0.8541	0.8124	0.7486

Table 3 shows the comparison of the performance of the proposed algorithm with other Gaussian denoising techniques in terms of Universal Image Quality Index (UIQI). It takes luminance, contrast and structure into account to assess the quality of the image compared to another image. The image is decomposed into block size of 8 for this purpose. The proposed method has comparable performance compared to other existing methods. Since all the methods produce UIQI value closer to 1 it indicates that the filtered image and the original image are almost close. INLM produces denoised image with very high UIQI value. Bilateral filter with method noise based thresholding and LPG-PCA follows the suit

Table 3
Comparison of UIQI Values of the Proposed Algorithm with other Existing Methods

	Cameraman Image				**Lena Image**			
Filters	**σ= 10**	**20**	**30**	**40**	**σ= 10**	**20**	**30**	**40**
Gaussian Filter	0.9814	0.9754	0.9475	0.9341	0.9998	0.9994	0.9987	0.9976
Wiener Filter	0.9648	0.9414	0.9143	0.9057	0.9997	0.9993	0.9988	0.9978
DWT	0.9309	0.9003	0.8793	0.8610	0.9990	0.9960	0.9888	0.9777
INLM	0.9982	0.9892	0.9786	0.9606	0.7764	0.6770	0.6093	0.5592
LPG-PCA	0.9312	0.9124	0.8826	0.8738	0.9891	0.9859	0.9798	0.9689
Bilateral Filter	0.9197	0.9008	0.8950	0.8895	0.9984	0.9965	0.9956	0.9945
Bilateral Filter +Method Noise	0.9438	0.9387	0.9278	0.9184	0.9901	0.9803	0.9723	0.9642
Proposed Method	0.9201	0.9320	0.9056	0.8935	0.9331	0.9158	0..08916	0.8691

Figure (2) shows the original image and its denoised version with standard deviation value of 10. Figure (3) shows the visual quality of the proposed algorithm together with other existing Gaussian noise removal techniques for the image corrupted by low noise. It is observed from the results that the edges and other details are preserved in the image filtered by the proposed algorithm compared to that of other traditional methods. The Gaussian filter smoothens the background building. It is depicted in figure 3a.

The Wiener filter output shown in figure 3b indicates more blurring affect. The cameraman is image blurred and background buildings are totally smoothened. The DWT based denoised image shown in figure 3c is of poor visual quality and the original image is not recovered properly. It is very difficult to distinguish minute differences under low noise density conditions; consequently, the visual effects of various denoising methods remain same.

Improved NLM output shown in figure 3d is very good with respect to human visual perception. Even though it offers very good performance it is computationally complex. Bilateral filter and method noise based bilateral filter based denoising images are shown in figure 3e and 3f. It is obvious from figure 3f the bilateral based denoised image has lost most of the details. Background information is completely missing. Those details are available in method noise based thresholding since it estimates the lost details. Figure 3g and 3h show the output of the LPG-PCA and BM3D filters. They also show very good denoising capability. The denoised image shown in figure 3i shows all the details and indicates very good contrast compared to all other algorithms. The background structures are clearly visible and edges are also preserved.

(a)

(b)

Figure 2: (a) Original image (b) Noisy image with σ=10

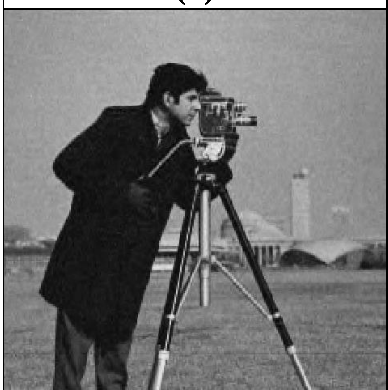
 **(a)**	 **(b)**	 **(c)**
 **(d)**	 **(e)**	 **(f)**
 **(g)**	 **(i)**	 **(i)**

Figure 3: Denosing results (a) Gaussian Filter (b) Wiener Filter (c) DWT with Bayesian shrinking (d) Improved NLM (e) Bilateral Filter (f) Bilateral Filter and its Method Noise (g) LPG-PCA filter (h) (i) BM3D filter (i) Proposed Algorithm

The image denoised with noise density of 40 is shown in figure 4b. The proposed algorithm and other filters are applied on the noisy image and the results obtained are shown in figure 5. Gaussian, Wiener and DWT techniques exhibit very poor denoising capability when noise density is increased. It is clearly visible in figure 5a,5b and figure 5c respectively. INLM denoising shown in figure 5d loses all the background details. Figure 5e and figure 5h show the output of bilateral and BM3D filter. They are completely blurred when noise density is increased. The denoised image from bilateral filter with method noise thresholding shown in figure 5f has some residual noise. Here too the proposed algorithm performs better than that of other denoising techniques since the lost details are estimated accurately and blended with the denoised image. Hence, the details are clearly visible in the filtered image as shown in figure 5i.

(a) **(b)**

Figure 4: (a) Original image (b) Noisy image with σ=40

(a) **(b)** **(c)**

e)

(d)

(f)

(g)

(h)

(i)

Figure 5: Denoised image for standard deviation of 10 (a) Gaussian Filter (b) Wiener Filter (c) DWT with Bayesian Shrinking (d) Improved NLM (e) Bilateral Filter (f) Bilateral Filter and its Method Noise (g) LPG-PCA filter (h) (i) BM3D filter (i) Proposed Algorithm

Conclusion

In this work, Gaussian noise removal in an image based on the Fast Guided Filter and its method noise thresholding is proposed. Its performance is analysed by both quantitatively and qualitatively. From the results it's concluded that the proposed algorithm performs well in both the aspects. PSNR, SSIM and UIQI are taken as metrics to analyse the filtering capability of the proposed algorithm qualitatively. It has less computational complexity and superior performance compared to other denoising algorithms. The visual quality of the proposed algorithm is also very good.

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