International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2017 IJSRCSEIT | Volume 2 | Issue 1 | ISSN : 2456-3307

Image Denoising using Bilateral Filter and Wavelet Thresholding

Sirisha B., K. Dhilli, E. Govinda

Department ECE, Avanthi Institute of Engineering and Technology, Narsipatnam, Visakhapatanam, Andhra Pradesh, India

ABSTRACT

In this work, a hybrid denoising algorithm which combines spatial domain bilateral filter and hybrid thresholding function in the wavelet domain is being proposed. The wavelet transform is used to decompose the noisy image into its different subbands namely LL, LH, HL, and HH. A two-stage spatial bilateral filter is applied. The first stage is applied to the noisy image before wavelet decomposition. This stage will be called a pre-processing stage. The second stage spatial bilateral filtering is applied on the low-frequency subband of the decomposed noisy image namely subbands LL. This stage will tend to cancel or at least attenuate any residual low-frequency noise components. The intermediate stage deal with high-frequency noise components by thresholding detail subbands LH, HL, and HH using hybrid thresholding function. The performance of the proposed denoising algorithm will be superior to that of the conventional denoising approach which may be proved after experimental analysis.
Keywords: Bilateral Filter, Wavelet Thresholding, Image Denoising

I. INTRODUCTION

Digital images play an important role in various applications such as satellite television, medical imagining, remote sensing, computer vision, pattern recognition etc. While collecting the information from the image sensors due to intrinsic (lens arrangement, lens distortion factors) and extrinsic parameters (atmosphere, human beings) of the camera device may chance have occurred the noise in the image. Furthermore, noise can be introduced by transmission errors and compression. Therefore, image denoising is a fundamental problem in the field of image processing. It is necessary to apply an efficient denoising technique to reduce the noise in the data.

Image denoising still remains a challenge for researchers because noise removal introduces artefacts and causes blurring of the images because of noise modelling in images is greatly affected by capturing devices, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are affected by Gaussian noise.This project introduces a novel algorithm to reduce noise in the image and evaluate the quality of the denoised image in terms of quality parameters.

The basic idea behind this thesis is the estimation of the uncorrupted image from the distorted or noisy image and is also known as image denoising. There are various techniques present to remove the noise from the corrupted image. Selecting the appropriate method plays a major role in getting the desired image. In this paper, a study is made on the various denoising algorithms like Gaussian/Bilateral filtering (GBF), GBF with wavelet thresholding (Wavelet threshold based GBF) and each technique is compared in terms of its quality parameters like PSNR (Peak Signal to Noise Ratio), IQI (Image Quality Index).

The rest of the work is presented as Section 2 deals with detail description of various existing denoising methods; Section 3 deals with the detail description of proposed algorithms; Section 4 deals with the detail description of results and discussions and Section 5 deals with the detail description of conclusion.

II. METHODS AND MATERIAL

A. Edge Preserving Filters

The main objective of image denoising is to remove the noise from the degraded image without preserving the image features like edges, details as much as possible.

B. Linear Filters

Linear filters are a well-known technique for removal of Gaussian or additive noise image. Linear filters, which consist of convolving the image with a constant matrix to obtain a linear combination of neighbourhood values. However, they can produce a blurred and smoothed image with poor feature localisation and incomplete noise suppression.

C. Gaussian Filter

Filters based on Gaussian functions are quite popular, because their shapes are easily specified and both the forward and inverse Fourier transforms of a Gaussian function are realGaussian functions. Further, if the frequency domain filter is narrower, the spatial domain filter will be wider which attenuates the low frequencies resulting in increased smoothing/blurring.These Gaussian filters are typical linear filters that have been widely used for image denoising.

In Gaussian filters, weight of the pixels is given by

$$G_{\sigma}(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} \quad (1)$$

Gaussian filters assume that images have smooth spatial variations and pixels in a neighbourhood have close values, by averaging the pixel values over a local neighbourhood suppresses noise while preserving image features. However, this assumption fails at edges where the spatial variations are not smooth. Due to that, the Gaussian filter blurs the edges. To overcome this problem we introduce a bilateral filter.

D. Bilateral Filter

The bilateral filter filtering the image in both range and space domain.Bilateral filtering is a local, nonlinear and non-iterative technique which considers both grey level similarities and geometric closeness of the neighbouring pixels.Mathematically,the bilateral filter output at a pixel location ‘p’ is calculated as follows

$$I_F(p) = \frac{1}{w} \sum_{q \in s} G_{\sigma_s}(\|p-q\|) G_{\sigma_r}(|I(p) - I(q)|)\, I(q) \quad (2)$$

Where $G_{\sigma_s}(\|p-q\|) = e^{-\frac{\|p-q\|^2}{2\sigma_s^2}}$ is a geometric closeness function

$G_{\sigma_r}(|I(p) - I(q)|) = e^{-\frac{|I(p)-I(q)|^2}{2\sigma_r^2}}$ is a gray level similarity function

W= Normalization constant

$\|p-q\|$is the Euclidian distance between ‘p’ and ‘q’.

and 's’ is a spatial neighbourhood of ‘p’.

The two parameters σ_s and σ_r controls the behavior of the bilateral filter. The optimal σ_s value is relatively insensitive tonoise variancecompared to the optimal value σ_r and is chosen based on the desired amount oflow-pass filtering.A large σ_s blurs more, i.e., it combines values from more distant image locations. Also, if an image is scaled up or down, σ_s must be adjusted accordingly in order toobtain equivalent results.It appears that a good range for the $\sigma_s$value is roughly [1.5 - 2.1]. On the other hand, the optimal σ_r value changes significantly as the noise standard deviation $\sigma_n$changes.

E. Gaussian Bilateral Filter And Wavelet Thresholding

The proposed method of image denoising uses the combination of Gaussian/Bilateral Filter and its Method noise Thresholding using wavelets (G/BFMT) and is shown in Figure 1. A difference between the original image and its denoised image shows the noise removed by the algorithm, is known as method noise.In principle, the method noise should look like a noise. Since even good quality images have some noise, it makes sense to evaluate any denoising method that way, w

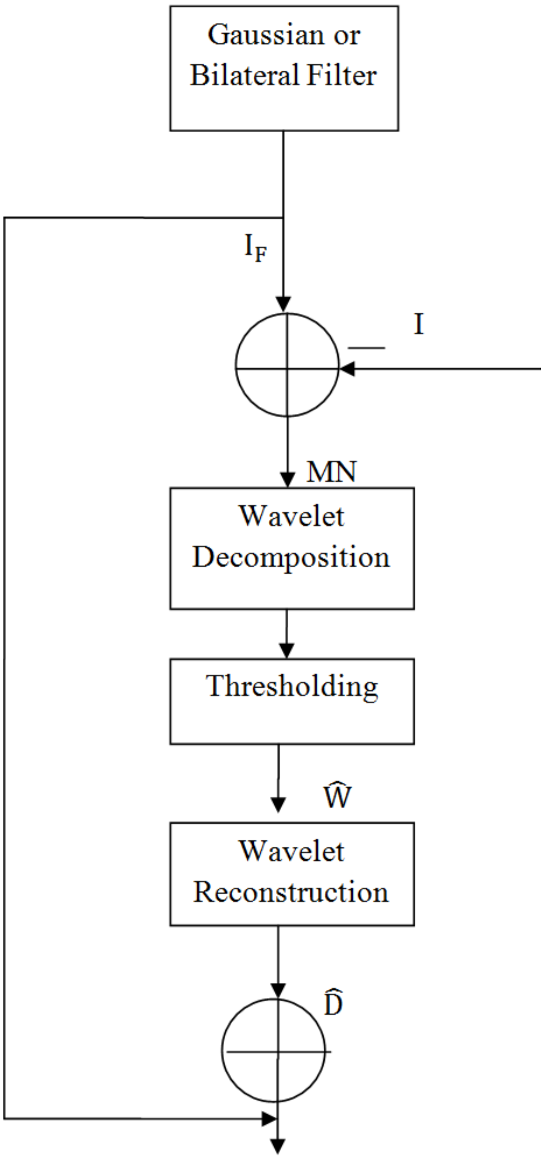


Figure 1: Proposed image denoising algorithm

$$MN = A - I_F \quad (3)$$

Where 'An' is the original image and$I_F$is the output of denoising operatorfor a input image 'A'.

F. Gaussian/Bilateral Filter

The bilateral filter on the noisy image averages the noise along with the image details while preserving edges/sharp boundaries very well provided the standard deviation of the noise is less than the edge contrast. In the case of the Gaussian filter, its method noise is zero inharmonic parts of the image and very large near edges or texture, where the Laplacian can not be small. As a consequence, the Gaussian convolution is optimal in flat parts of the image bulges and texture is blurred. To capture what is removed from the noisy image by theGaussian/Bilateral filter, the definition of the method noise is redefined as the difference between the noisy image and its denoised image. Hence, Equation (4.3) is rewritten as

$$MN = I - I_F \quad (4)$$

Where I= A + Z is a noisy image obtained by corrupting the original image 'A' by a whiteGaussian noise 'Z' andI_F is the output of Gaussian/Bilateral filter for a input image I.

Since the Gaussian/Bilateral filter has removed the noise as well as image details by averaging the pixels, the method noise will consist of noise as well as image details along with some edges. The method noise due to Gaussian filtering will have more strong edges as compared to that of bilateral filtering as the edges are preserved by range filtering σ_r. So, the methodnoise 'MN' is a combination of image details 'D' and a white Gaussian noise 'N' and is written as

$$MN = D + N \quad (5)$$

Now the problem is to estimate the detail image 'D', which has only the original image features and edges/sharp boundaries that are removed by Gaussian/Bilateral filter, as accurately as possible according to some criteria and is added to the Gaussian/Bilateral filtered image I_F to get better denoised image with details. In wavelet domain, Equation (5) can be represented as

$$Y = W + N_W \quad (6)$$

Where 'Y' is the noisy wavelet coefficient (method noise), 'W' is the true wavelet coefficient(detail image) andN_W is independent Gaussian noise.

G. Wavelet Thresholding

In wavelet domain, the goal is to estimate the true wavelet coefficient 'W' from 'Y' by thresholding 'Y' with a proper value of threshold which minimises MSE so that it can retain the original image features and edges/sharp boundaries very well in the final denoised image. The estimate of the true wavelet coefficient is represented as$\widehat{W}$ and its wavelet reconstruction gives an estimate of the detail image$\widehat{D}$. The summation of this detail image $\widehat{D}$ with theGaussian/Bilateral filtered image I_F will give the denoised image 'B', certainly have more imagedetails and edges as compared with Gaussian/Bilateral filtered image I_F.

Wavelet thresholding adds power to the proposed method as noise components can be eliminated better in detail subbands of method noise. As BayesShrink provides a better MSEperformance than SureShrink, it is used in the proposed method to threshold the method noisy wavelet coefficients. BayesShrink is also an adaptive, data-driven thresholding strategy via soft-thresholding which derives the threshold in a Bayesian framework assuming a generalizedGaussian distribution. This method is adaptive to each sub-band because it depends on data-driven estimates of the parameters. The threshold for a given subband derived by minimizingBayesian risk and is given by

$$T = \frac{\sigma^2}{\sigma_w} \quad (7)$$

Where σ^2 is the noise variance estimated from subband HH_1 by a robust median estimator givenby

$$\hat{\sigma} = \frac{Median\left(|Y_{i,i}|\right)}{0.6745}, Y_{i,i} \in \{HH_1\} \qquad (8)$$

And σ_w^2 is the variance of wavelet coefficients in that subband, whose estimate is computedusing

$$\hat{\sigma}_w^2 = max\left(\hat{\sigma}_y^2 - \hat{\sigma}^2, 0\right) \qquad (9)$$

Where $\hat{\sigma}_y^2 = \frac{1}{MN}\sum_{i,j=1}^{M,N} Y_{i,j}^2$

H. Quality Metrics

In this section, we will discuss various image quality measurements to find out the quality of a denoised image obtained from different restoration methods as we discussed in chapter 4.

Mean Square Error (MSE)

The the mean square error is used as a part of the digital image processing method to check for errors .two MSEs are calculated and then compared to determine the accuracy of an image. In statistics, the mean squared error mean squared deviation (MSD) of an estimator measures the average of the squares of the error or deviation, that is, he difference between the estimator and what is estimated.The difference occurs because of randomness or because the estimator does not account for information that could produce a more accurate estimate.

Let f(x, y) and g (x, y) represents original image and denoised image with a dimension M*N, then Mean square error is given by

$$\mathrm{MSE} = \frac{1}{\mathrm{MN}}\sum_{\mathrm{x}=1}^{\mathrm{M}}\sum_{\mathrm{y}=1}^{\mathrm{N}}(\mathrm{f}(\mathrm{x},\mathrm{y}) - \mathrm{g}(\mathrm{x},\mathrm{y}))^2 \qquad (10)$$

Peak Signal to Noise Ratio (PSNR)

PSNR is defined as the ratio between the maximum possible power of a signal and the power of the corrupting noise that affects the fidelity of its representation because many signals have a very wide dynamic range. PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs(eg :for image compression).

Let f(x, y) and g (x, y) represents original image and denoised image with a dimension M*N, then Peak signal to noise ratio is given by

$$\mathrm{PSNR} = 10\log_{10}\left({255^2}/{\mathrm{MSE}}\right) \qquad (11)$$

Image Quality Index (IQI)

Let f(x, y) and g (x, y) represents original image and denoised image with a dimension M*M then Image Quality Index (IQI) is given by

$$\mathrm{IQI} = \frac{4\sigma_{\mathrm{fg}}\bar{\mathrm{f}}\bar{\mathrm{g}}}{(\sigma_{\mathrm{f}}^2+\sigma_{\mathrm{g}}^2)[\bar{\mathrm{f}}^2+\bar{\mathrm{g}}^2]} \qquad (12)$$

Where $\bar{\mathrm{f}} = \frac{1}{\mathrm{M}}\sum_{\mathrm{x}=1}^{\mathrm{M}}\mathrm{f}_{\mathrm{x}}$ and $\bar{\mathrm{g}} = \frac{1}{\mathrm{M}}\sum_{\mathrm{x}=1}^{\mathrm{M}}\mathrm{g}_{\mathrm{x}}$

$\sigma_{\mathrm{f}}^2 = \frac{1}{\mathrm{M}-1}\sum_{\mathrm{x}=1}^{\mathrm{M}}(\mathrm{f}_{\mathrm{x}} - \bar{\mathrm{f}})^2and\sigma_{\mathrm{g}}^2 = \frac{1}{\mathrm{M}-1}\sum_{\mathrm{x}=1}^{\mathrm{M}}(\mathrm{g}_{\mathrm{x}} - \bar{\mathrm{g}})^2$

III. RESULTS AND DISCUSSION

In this section, we are going to discuss the simulation results of various techniques like WT, BF, GF and BFWT. Figure 2 represents the dataset for image denoising with 512*512 resolution.

a) barbara

b) Penguins

c) siri

d) manvi

Figure 2 : Data Set for image denoising

Table 1 : Quality Parameters for various images using GF

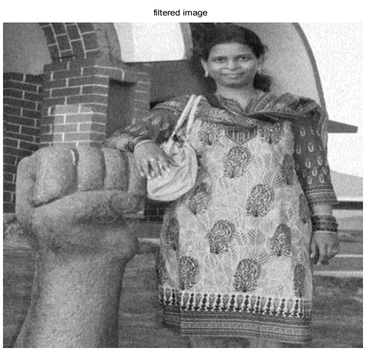
	sigma	10	20	30	40	50
siri	PSNR	28.9685	22.2157	18.7600	16.3744	14.6085
	IQI	0.9808	0.9355	0.8819	0.8320	0.7893
manvi	PSNR	28.1309	22.1439	18.7248	16.3883	14.6608
	IQI	0.9811	0.9438	0.9035	0.8631	0.8258
barbara	PSNR	28.1306	22.1386	18.7105	16.3744	14.6518
	IQI	0.9883	0.9570	0.9147	0.8708	0.8309
Penguins	PSNR	28.2253	22.2984	18.8797	16.5144	14.7546
	IQI	0.9830	0.9560	0.9267	0.8919	0.8622

Table 2 : Quality Parameters for various images using BFWT

	sigma	10	20	30	40	50
siri	PSNR	31.0438	27.4343	25.3281	23.6965	22.3539
	IQI	0.9894	0.9775	0.9639	0.9486	0.9312
manvi	PSNR	33.6228	29.8053	27.1330	25.0841	23.4525
	IQI	0.9942	0.9864	0.9760	0.9639	0.9508
barbara	PSNR	34.7687	30.4446	27.4958	25.3135	23.6166
	IQI	0.9968	0.9925	0.9857	0.9767	0.9656
Penguins	PSNR	31.9113	28.1319	25.7982	24.0357	22.5942
	IQI	0.9924	0.9840	0.9747	0.9615	0.9525

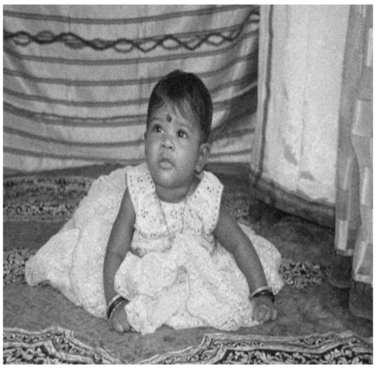
By observing Table 6.1 and Table 6.2 and comparing the quality parameters PSNR and IQI we can infer that Bilateral Filter with the method of Wavelet Thresholding provides better filtering compared to Guided Filter.

Figure 3 represents the GF, BFWT filtering images of siri, manvi and Barbara by using db8 wavelet with soft thresholding.

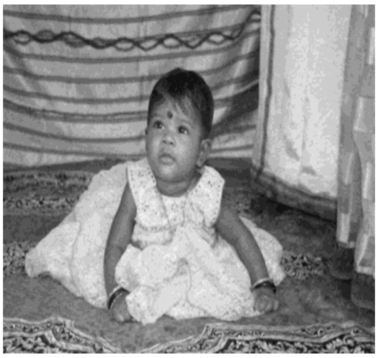


a) Guided Filtering of siri Image

b) BFWT of siri Image



c) Guided filtering of manvi image



d) BFWT of manvi image

e) Guided filtering of barbara image

f) BFWT of Barbara image

Figure 3 : GF and BFWT of different images

Table 3 : PSNR of GF and BFWT under different wavelets for Penguins image

	sigma	10	20	30	40	50
GF		28.2253	22.2984	18.8797	16.5144	14.7546
BFWT	Db8	31.9113	28.1319	25.7935	24.0357	22.5942
	Sym8	31.9687	28.1445	25.8056	24.0353	22.5934
	Db16	31.9392	28.1300	25.7935	24.0357	22.5969
	Coif5	31.9731	28.1280	25.7910	24.0334	22.5958
	Bior6.8	32.0850	28.1317	25.7027	23.8672	22.3939

Table 4 : IQIof GF and BFWT under different wavelets for Penguins image

	sigma	10	20	30	40	50
GF		0.9830	0.9560	0.9267	0.8919	0.8622
BFWT	Db8	0.9924	0.9840	0.9747	0.9615	0.9525
	Sym8	0.9923	0.9840	0.9747	0.9614	0.9525
	Db16	0.9924	0.9841	0.9747	0.9614	0.9526
	Coif5	0.9923	0.9839	0.9746	0.9613	0.9525
	Bior6.8	0.9924	0.9838	0.9739	0.9602	0.9506

It is known that different wavelets like Db8, Sym8, Db16, Coif5 and Bior6.8 are used to decompose the method noise. The performance of Wavelet based denoising method depends on the type of wavelet used. In order to analyse the effect different wavelets like db8, sym8, db16, coif5 and bior6.8 are used to decompose the method noise in BFWT. PSNR and IQI of the denoised image of Penguins by GF and BFWT with different wavelets are tabulated in Tables 6.3 and 6.4 respectively. The values in these tables show the highest PSNR and IQI of the denoised images by different wavelets.

It is observed from the Table 6.3 and 6.4 that, BFWT provides better performance compared to GF. It is also clear from table 6.3 and 6.4 that for various decompositions the PSNR and IQI are better for Bior6.8, Db8 in many cases.

Table 5 : Comparison of GF, BFWT with different thresholding techniques for manvi image

	Sigma	10	20	30	40	50
GF	PSNR	28.1309	22.1439	18.7248	16.3883	14.6608
	IQI	0.9811	0.9438	0.9035	0.8631	0.8258
BFWT with soft thresholding	PSNR	33.6228	29.8053	27.1330	25.0841	23.4525
	IQI	0.9942	0.9864	0.9760	0.9639	0.9508
BFWT with hard thresholding	PSNR	32.7921	29.6732	27.1006	25.0602	23.4351
	IQI	0.9928	0.9862	0.9759	0.9638	0.9507

The above table 6.5 compares GF and BFWT with soft thresholding and BFWT with hard thresholding techniques for manvi image. The quality parameters PSNR and IQI are tabulated. From the table, we can observe that BFWT with soft thresholding provides better performance compared to GF and BFWT with hard thresholding.

IV.CONCLUSION

In this work, the combination of bilateral filter and its method noise thresholding using wavelets has been proposed. The performance of the proposed methods is compared with guided filter, BF, based methods. Through experiments conducted on standard images, it was found that, BFWT has shown a good denoising performance in terms of PSNR, IQI but at the cost of increased computational complexity. With lesser computational complexity, the proposed methods have shown a similar performance as that of WT and superior/comparable performance to that ofBF and Guided filter based methods, in terms of method noise PSNR and IQI.

V. REFERENCES

[1]. Scott E Umbaugh, "Computer Vision and Image Processing", Prentice Hall PTR, New Jersey, 1998.

[2]. Langis Gagnon, "Wavelet Filtering of Speckle Noise-Some NumericalResults," Proceedings of the Conference Vision Interface 1999, Trois-Riveres.

[3]. Motwani, M.C., Gadiya, M. C., Motwani, R.C., Harris, F. C Jr. "Survey of Image Denoising Techniques".

[4]. J.N. Lin, X. Nie, and R. Unbehauen, "Two-Dimensional LMS Adaptive Filter Incorporating a Local-Mean Estimator for Image Processing," IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing, Vol 40, No.7 July 1993, pg. 417-428.

[5]. Survey of Image Restoration Techniques by P.K. Murphy

[6]. Fundamentals of digital image processing by Anil. K. Jain

[7]. H. Zhang, Aria Nosratinia, and R. O. Wells, Jr., "Image denoising via wavelet-domain spatially adaptive FIR Wiener filtering", in IEEE Proc. Int. Conf. Acoust., Speech, Signal Processing, Istanbul, Turkey, June 2000.

[8]. Kim, J.-Y., L.-S. Kim, et al., "An advanced contrast enhancement using partially overlapped sub-block histogram equalization," IEEE Trans. Cir. and Sys. for Video Technol. Vol. 11, pp. 475–484.

[9]. C. Leung, K.-S. Chan, H. Chan, W. Tsui, "A new approach for image enhancement applied to low-contrast–low-illumination IC and document images," Pattern Recognition Letters, vol. 26 (6) (2005), pp. 769–778