Novel Image Denoising with Method Noise Thresholding using Statistical Nearest Neighbor Filter

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Abstract
The goal of this research is to offer a novel denoising approach for generating a denoised image(s) having fewer artifacts and improved efficiency at higher noise levels. Statistical Nearest Neighbor with Method Noise Thresholding (SNNMNT) is a new filter that improves the quality of the final image. Aside from direct filtering, the noisy image and pre-filtered image would be used to generate method noise in this work. This method employs Neighshrinksure estimation to make wavelet filtering. These computed values are then added to the prefiltered image to produce the desired resulting image. The noisy image is denoised without losing the original image details for precise analysis and extraction of image features. The benchmark images denoised with standard deviation (σ=10) using bior6.8 wavelet when filtered using earlier filters such as Gaussian Bilateral Filter with Method Noise Thresholding and Statistical Nearest Neighbor show improvement resultant image quality in terms of PSNR and ISSN as compared to the proposed filtering technique. The proposed filter produces higher PSNR and ISSN values (PSNR=34.49 and SSIM=09997). This functional filter proposed in this work provides an improvement in image quality parameters of the image when compared with the earlier methods. The pictorial analysis was also carried out in the present work.

Keywords:
Method Noise, Wavelet Thresholding, Wiener Filter, and Statistical Nearest Neighbor.

1. Introduction

Normally, digital images are contaminated during image acquisition, processing, preservation, compression, and transmission and are called noisy images. Most of the noisy gray or color images are corrupted with Gaussian noise due to poor illumination and higher temperature in hardware circuitry. Thus, images corrupted with Gaussian noise are used as the standard noisy images to evaluate the effectiveness of the image denoising algorithm. The main aim of image denoising is for enhancing the image's visual quality and preserve the complex structures and precious image details like textures and edges [1,2]. Image denoising has been one of the important research activities among researchers working in the image processing area. Isabel V Hernández-Gutiérrez et al. [3] states descriptors evaluation for each search window in the noisy image to apply statistical neighborhood pre-classification with respect to the homogeneity of each window to distinguish whether the noisy current pixel is in the homogeneous region or it is in an edge object region. Their result shows that considerably reduces processing time from 8 through 15 times in comparison with standard NL means filters. K. Zhang et al. [4] developed an FFDNet model that effectively eliminates spatially variant noise but over smoothing the image details are the major issue. L. Fan et al. [5] developed a filter that preserves more image details but is inefficient in deblurring and higher expensive computation. H. R. Shahdoosti and S.M. Hazavei [6] a block-matching algorithm with a hard thresholding operator will provide effectively a noise-free image with higher memory and time consumption. C. Tian et al. [7] developed a filter that simplifies the system complexity but an ill-posed denoising issue arises in this study. Kaixin Chen et al. [8] suggested a method to reduce the rician noise formed in MR imaging using adaptive NL means filter and fuzzy C-means clustering. Other contemporary methods reduce only Gaussian noise with more computational time and cost. In the process of recovering the original image from the noisy image, several denoising techniques/methods have been proposed**.** Non Local Means(NLM) is a conceptually simple denoising algorithm widely used by researchers during image denoising.

In the present work, Method Noise Thresholding (MNT) technique is adopted along with the SNN filter to further improve the quality of the denoised image. The proposed novel noise filtering technique shows improvement in Peak Signal-to-Noise Ratio(PSNR), particularly for lower standard deviation(σ < 30) values.

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The paper is organized as follows. Section deals with the Statistical Nearest Neighbor filtering technique. Method noise is dealt with in section 3. Section 4 elaborates the proposed method with a block diagram. Section 5 dealt with the proposed method for different wavelets and different filters. Section 6 makes results and discussion. Section 7 concludes the present work.

2. Statistical Nearest Neighbour (SNN)

This denoising filter proposed by Iuri et al shows improvement in the perceived image quality as far as white and colored Gaussian noise and is also used as a bilateral filter [9,10]. In this technique, the Gaussian noise image with variance(σ^2) is obtained, and then a search for similar patches is carried out to obtained the distances of the similar patches using the expression;

$$d^2(\mu, \gamma_k) = \left(\frac{2\sigma^2}{P}\right) \times \sum_{i=0}^{P-1} G(0,1)^2 \quad (1)$$

Where, σ^2 - variance, μ - mean, G(μ ^{2}) - Gaussian random value and γ_k- neighborhood patch.

Sum of squared normal value P has x_P^2distribution $d^2(\mu, \gamma_k) \sim \left(\frac{2\sigma^2}{P}\right) \times x_P^2$.

hence,

$$E[(\mu, \gamma_k)] = 2\sigma^2 \quad (2)$$

SNN technique introduced supports intuition with analytical evidence which is easy to control. Here, a simplified toy concern is described, where the reference patch 1 x 1 with μ is contaminated by σ^2 with variance μ_rG(μ, σ^2)

whereμ_r- noisy reference patch.

The probability P and cumulative density functions ϕ are mathematically stated in equations (3) and (4).

$$P(\mu_r < x) = \phi_{\mu,\sigma^2}(x) = \frac{1}{2} \times \left[1 + erf\left(x - \frac{\mu}{\sqrt{2\sigma}}\right)\right. \quad (3)$$

$$\phi_{\mu,\sigma^2}(x) = \Phi'_{\mu,\sigma^2}(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-0.5}\left[\frac{x-\mu}{\sigma}\right]^2 \quad (4)$$

Let N be the noisy neighbors $\{\gamma_k\}, k = 1, \dots \dots N$, where N replicas of μ and it are distributed as G(μ, σ^2). The probability P and cumulative density functions ϕ $\{\gamma_r\}, k = 1, \dots \dots N$ are mathematically denoted as shown in equations (5) and (6) respectively.

$$P(\gamma_k < x) = \Phi_{mix}(x) = p_r \Phi\mu, \sigma^2(x) + p_f \Phi_{\mu f, \sigma^2}(x) \quad (5)$$

$$\phi_{mix}(x) = \Phi_{mix}(x)' = p_r \phi_{\mu,\sigma^2}(x) + p_f \phi_{\mu f, \sigma^2}(x) \quad (6)$$

The simplified estimator $\mu(\mu_r)$ is expressed as shown in equation (7).

$$\mu(\mu_r) = \frac{1}{N_n} \sum_{k=1 \dots N_n} \gamma_k \quad (7)$$

Where, p_f- false matches, G(μ_f, σ^2) - distribution, andγ_k- noisy neighbor patch[aa].

The error prediction $\mu(\mu_r)$ is decomposed into variance and bias terms for a reference patch μ_r and its mathematical derivations are obtained using equations (8) (9) and (10).

$$\epsilon^2(\mu_r) = \int \mu(\mu_r - \mu)^2\, p(\mu) d\mu = \epsilon^2_{bias}(\mu_r) + \epsilon^2_{var}(\mu_r) \quad (8)$$

$$\int (E[\mu] - \mu)^2 p(\mu) d\mu = \{E[\mu(\mu_r) - \mu]\}^2 \quad (9)$$

$$\epsilon^2_{var}(\mu_r) = \int \mu(\mu - E[\mu])^2\, p(\mu) d\mu = Var[\mu(\mu_r)] \quad (10)$$

For notation clarity, eliminate the dependency of $\mu(\mu_r)$ from μ_r within the integrals and $p(\mu)$ is the probability density function of μ. T total error of the estimator is computed using the distribution of μ_r, as shown in the equations (11), (12), and (13).

$$\epsilon^2 = \epsilon^2_{bias} + \epsilon^2_{var} \quad (11)$$

$$\epsilon^2_{bias} = \int_{\mu_r} \epsilon^2_{bias}(\mu_r) \phi_{\mu,\sigma^2}(\mu) d\mu_r \quad (12)$$

$$\epsilon^2_{var} = \int_{\mu_r} \epsilon^2_{var}(\mu_r) \phi_{\mu,\sigma^2}(\mu_r) d\mu_r \quad (13)$$

The expression$\{\gamma_r\}, k = 1, \dots \dots N$ comprises N_n samples and their neighbors are collected using the NN methodology. The estimation error is computed using the statistical distribution of $E[\mu(\mu_r)]$ and $Var[\mu(\mu_r)]$. Let $\delta = |\gamma N_n(\mu_r) - \mu_r|$ be the distance of N_n^{th} the nearest neighbors μ_r. Other than the normalization factor ξ,each γ_k is independent of other factors. The probability density function $p(\delta)$ describes the probability of identifying Nn samples with the distance $\delta\ \mu_r$ that is defined in equation (14).

$$p(\delta) = \xi \times ptn(\delta)^{N-N_n} P_{bou}(\delta)[1 - ptn(\delta)]^{N-N_n} \quad (14)$$

Where,

$$ptn(\delta) = \Phi_{mix}(\mu_r + \delta) - \Phi_{mix}(\mu_r - \delta)$$

$$p_{bou}(\delta) = \phi_{mix}(\mu_r - \delta) - \phi_{mix}(\mu_r + \delta)$$

The normalization factor ξ is obtained by equating $\int_0^k P(\delta)d\delta = 1$.

Using equation (14) expected values $E[\mu(\mu_r)]$ are computed as shown in equation (15).

$$E[\mu(\mu_r)] = \frac{\Delta\delta}{N_n} \sum \delta \sum_{k=1 \dots N_r} E\left[\frac{\gamma_k}{\delta}\right] \times p(\delta) \quad (15)$$

Every N_n neighbors of γ_k lies in $[\mu_r - \delta, \mu_r + \delta]$ after marginalizing over δ.

The expected value $\mu(\mu_r)$ is then calculated using equation 15. To compute the variance $\mu(\mu_r)$, again marginalize the value δ and is mathematically denoted as shown in equation (16).

$$Var[\mu(\mu_r)] = \int_{-\infty}^{+\infty} (\mu - E[\mu])^2 p(\mu) d\mu$$

$$= \int_{-\infty}^{+\infty} (\mu - E[\mu])^2 \int \left\{p\left(\frac{\mu}{\delta}\right) p(\delta) d\delta\right\} d\mu$$

$$= \int_0^{+\infty} \left\{\int_{-\infty}^{+\infty} [(\mu - E[\mu])^2 p\left(\frac{\mu}{\delta}\right) d\mu\right\} p(\delta) d\delta] \quad (16)$$

Numerical integration is restored by adding and subtracting $E[\frac{\mu}{\delta}]$as represented in equation (17).

$$Var[\mu(\mu_r)] \cong \Delta\delta \sum_{\delta} \sum_{k=1 \dots N_n} \left\{ \left(\frac{var\left[\frac{\gamma_k}{\delta}\right]}{N_n^2} + (E[\frac{\gamma_k}{\delta}] - E[\mu] \right)^2 \right\} p(\delta) \quad (17)$$

The SNN patch $\{\gamma_r\}, k = 1, \dots, N$ is minimized using equation (18).

$$|d^2(\mu_r, \gamma_k) - o.2\sigma^2|, o = 1 \quad (18)$$

where o- additional offset parameter.

$Var[\mu(\mu_r)]$ and $E[\mu(\mu_r)]$ are computed for comparing the prediction error of SNN and NN and Fischer's approximation $(\sqrt{2x_p^2} \cong G\sqrt{2P-1}, 1)$ is applied in equation (1) for a single patch P=1.

$$d^2(\mu_r, \gamma) \cong \sigma \times \sqrt{2P-1} + G(0, \sigma^2) = \sigma + G(0, \sigma^2) \quad (19)$$

Though the SNN technique effectively diminishes the prediction error of the noise-free patches with a low signal-to-noise ratio, it is not optimal for noisy images which contain small features of interest.

3. Method Noise Thresholding(MNT)

Used along with classic image filters such as Gaussian filter, Neighbourhood filter, Statistical Nearest Neighbour filter improve the quality of the denoised image. Method noise is the image difference between the image(u) and the denoising operator(D_h) [11]. Here 'the filtering parameter and its selection depends on the noise variance(σ^2) and is the measure of the degree of filter applied to the image.

Decomposition of the image(v) is given by;

$$v = D_h v + n(D_h, v) \quad (20)$$

where

$D_h v$is more smooth than v

$n(D_h, v)$ is the noise guessed by the method.

Method Noise$n(D_h, u) = u - (D_h, u)$

Method noise is very small for non-noisy images and it contains small information about the original image.

4. Proposed Method

Fig. 1 shows the block diagram of the proposed work. Initially, the noisy image is filtered using statistical nearest neighbor (SNN) to obtain prefiltered image I_F. The difference between the noisy image I, and the denoised I_F image shows the noise removed by the algorithm, which is called the method noise. Residue value comprises noise as well as image details, and the same will be used to estimate the wavelet coefficients. Wavelet decomposition with the Neighshrinksure technique will be employed to get better performance. After inverse wavelet transform add these components to the prefiltered value I_F to get the resultant denoised image. The description of the proposed work to obtain a denoised image is as follows.

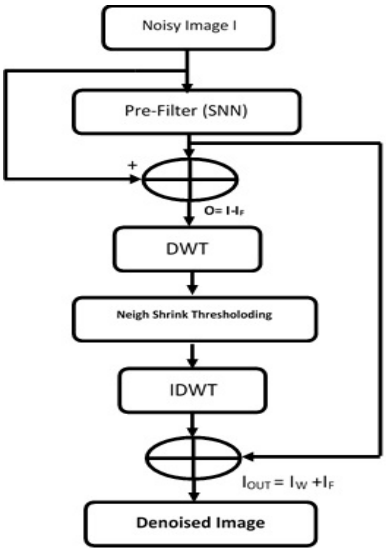

Fig. 1 Block diagram of the proposed method.

The noisy image (I) is initially applied to SNN filter to obtain a pre-filtered image (I_F). Method noise (O) is obtained from summing block-1 by computing the difference between pre-filtered image (I_F) and noisy image (I). Method noise is then applied to discrete wavelet transform (DWT) to obtain decomposed images up to three levels. NeighShrink thresholding eliminates the noisy components at the output of the DWT. The image is decomposed into wavelet components after thresholding are reconstructed using inverse discrete wavelet transform (IDWT) (I_W). The I_F image and I_W are combined using summing block-2 to obtain the denoised image. Fig. 1 shows the block diagram representation.

Lena, Barbara, and Zelda images are used as standard images in this study and are shown in Fig.2. (Source of Image Dataset: http://www.imageprocessingplace.com/root_files_V3/image_databases.htm) Pictorial analysis of the proposed work in different stages is shown in Fig. 3 and Fig. 4 for σ=10 and 20 respectively. Fig. 3 I represents the noisy image and I_F represents prefiltered image whereas, O represents method noise which is obtained by $O = I - I_F$. After wavelet thresholding image features will be represented as Iw, same will be added to the prefiltered image to obtain final denoised image i.e., $Iout = Iw + I_F$.

Fig. 2 Standard Images. a) Lena.png b) Barbara.png c) Zelda.png

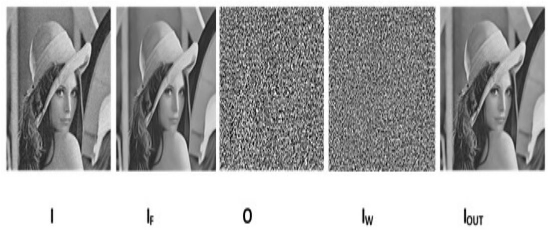

Fig. 3Lena Image at different stages in the proposed work for σ=10

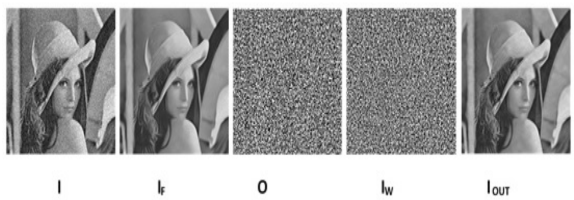

Fig. 4 Lena Image at different stages in the proposed work for σ=20

5. Implementation of the proposed filter(SNNMNT) for different standard images and filtering methods:

5.1 Proposed method for different wavelets

Implementation of a suitable filtering tool in the prefilter section to obtain a good filtered image (I_F) from the noisy image is the first step in the image denoising process. The prefiltered image does not provide all details of the original image and some of the important details of the original image such as border details, edge details, etc., of the image may be eliminated. Recovering these important details from the noisy image is of prime importance to get an accurate denoised image. In the present study instead of extracting the important details of the noisy image directly by wavelet thresholding technique filter (I_F)

image and noisy image (I) are subtracted through summing block to obtain a difference image called method noise image (O). Where O= I-I_F. Method noise is then subject to thresholding also called the denoised process. The selection of wavelet and threshold selection tool is of prime importance in the extraction of important components in improving the quality of the denoised image.

Selection of suitable wavelet in wavelet denoising that includes decomposition, wavelet thresholding, and reconstruction is an initial and important stage in the image denoising process. The quality of the denoised image is mainly measured through its PSNR value and the greater the PSNR value close will be the image details to the original image. The performance of six different wavelets (db4, db8, sym5, coif5, and bior6.8) in terms of PSNR is studied for three different images (Lena, Barbara, Zelda) and is tabulated as shown in Table 1. PSNR values of three standard images for different wavelets with varying standard deviation (σ=10 to 50) are tabulated and analyzed. It is learned from the table that the bior6.8 wavelet implemented in the proposed filter (SNNMNT) indicates an improvement in PSNR values for the three standard images. But the PSNR value analyzed with reference to standard deviation (σ) shows improved PSNR values for σ<= 30. In the following studies, the bior6.8 wavelet is considered for image denoising in the proposed filtering technique. Figure (5)-(7) shows the three standard images at different sigma values for the proposed method with bior6.8.

Table 1: Comparison of PSNR values for different wavelets.

	10	20	30	40	50
	Input Image: Lena				
Db8	34.28	30.57	28.47	26.82	25.51
Sym8	34.33	30.56	28.41	26.83	25.51
Db16	34.24	30.49	28.39	26.80	25.49
Coif5	34.32	30.54	28.35	26.80	25.50
Bior6.8	**34.49**	**30.67**	**28.45**	**26.83**	**25.48**
	Input Image: Barbara				
Db8	33.09	30.03	28.06	26.39	24.95
Sym8	33.16	30.04	28.07	26.40	24.95
Db16	33.05	30.03	28.06	26.39	24.95
Coif5	33.11	30.16	28.11	26.44	25.03
Bior6.8	**33.43**	**30.16**	**28.11**	**26.44**	**25.03**
	Input Image: Zelda				
Db8	35.47	31.62	29.16	27.28	25.82
Sym8	35.47	31.62	29.15	27.29	25.84
Db16	35.46	31.58	29.18	27.32	25.87
Coif5	35.56	31.64	29.20	27.35	25.88
Bior6.8	**35.61**	**31.65**	**29.17**	**27.27**	**25.63**

Fig. 5 Lena Image denoised with proposed method (bior6.8) for σ = 10,20,30,40 and 50.

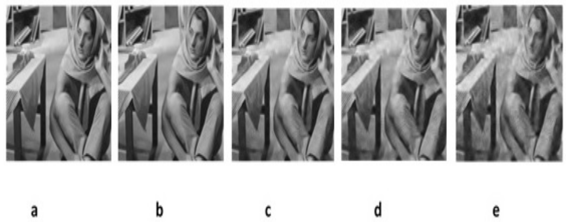

Fig. 6 Barbara Image denoised with proposed method (bior6.8) for σ = 10,20,30,40 and 50.

Fig. 7 Zelda Image denoised with proposed method (bior6.8) for σ = 10,20,30,40 and 50.

5.2 Proposed method for different image filters

As discussed in present and earlier SNN filter adopted in the prefilter stage and the bior6.8 wavelet used in wavelet denoising when processed through the method noise thresholding technique shows improvement in quality of the denoised image providing high PSNR values. The validity of the proposed novel filter (SNNMNT) is tested by denoising the standard images of Lena, Barbara, and Zelda with existing image denoising methods such as WT, GBFMT, WFMNT, NSS, ANL, and SNN along with SNNMNT denoising method. Table 2 shows PSNR values of denoised images of standard images subjected to different standard deviations (σ) varied from 10 to 50. Table 2 depicts that improved PSNR values are observed for images with lower standard deviation (σ<=30) and for higher values PSNR slightly reduces. Graphical representation of variations in PSNR values with different noise standards for three standard images is shown in Fig. 8. Denoised images of Lena with noise standards obtained by different filters along with the proposed method are shown in Fig. 9.

Table 2: Comparison of PSNR values for the different methods with the proposed one.

σ	10	20	30	40	50
Method Used	**Input Image: LENA**				
WT	29.59	26.54	24.88	23.93	23.42
GBFMT	33.07	29.23	27.19	25.76	24.69
WFMNT	33.23	28.94	26.71	25.13	23.79
NSS	33.56	29.48	27.35	25.89	24.74
ANL	33.68	30.22	28.08	26.33	24.80
SNN	32.45	30.10	28.37	26.89	25.56
Proposed	**34.49**	**30.68**	**28.46**	**26.83**	**25.48**
	Input Image: BARBARA				
WT	28.29	25.59	24.19	23.32	22.58
GBFMT	31.78	28.33	26.53	25.27	24.26
WFMNT	32.10	28.31	26.21	24.72	23.48
NSS	32.48	28.58	26.59	25.21	24.20
ANL	32.49	29.04	26.98	25.39	23.95
SNN	32.37	29.91	28.01	26.31	24.68
Proposed	**33.43**	**30.16**	**28.11**	**26.44**	**25.03**
	Input Image: ZELDA				
WT	29.89	27.93	26.98	26.37	25.51
GBFMT	34.39	30.89	28.65	27.17	25.83
WFMNT	34.44	30.32	27.87	25.89	24.37
NSS	35.10	31.33	29.29	27.77	26.57
ANL	34.76	30.94	28.32	26.22	24.58
SNN	34.34	31.27	28.76	26.67	24.92
Proposed	**35.61**	**31.65**	**29.17**	**27.27**	**25.63**

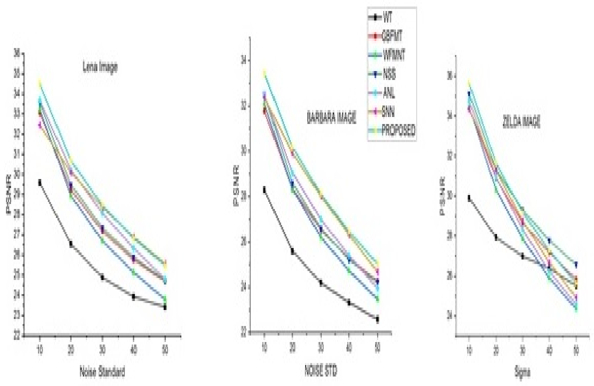

Fig. 8 Graphical analysis of PSNR for different images for a) Lena b) Barbara c) Zelda

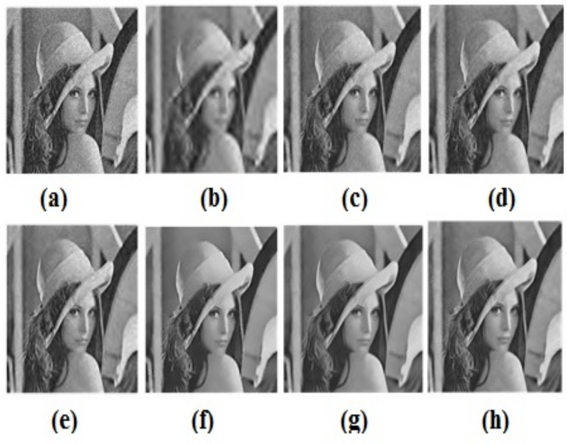

Fig. 9 Noisy image σ=20; b) WT, c) GBFMT, d) WFRT e)NSS f) ANL g) SNN h) Proposed Method.

5.3 SSIM and IQI

Other features of denoised images such as Structural Similarity Index Module (SSIM) and Image Quality Index are also measured for the proposed filter. Table. 3 shows SSIM values of Lena image filtered using different denoising methods and varying standard deviation. SSIM value obtained through the proposed method is slightly greater for σ<=30 and is the same for higher values. IQI value measured for three standard images for different noise standards is represented in Table 4.

Table 3: Comparison of SSIM values for the proposed method.

σ	10	20	30	40	50
Method Used	**Input Image: LENA**				
WT	0.9993	0.9988	0.9985	0.9983	0.9982
GBFMT	0.9996	0.9992	0.9989	0.9986	0.9984
WFMNT	0.9996	0.9992	0.9989	0.9986	0.9982
NSS	0.9996	0.9993	0.9990	0.9987	0.9985
ANL	0.9996	0.9993	0.9990	0.9988	0.9985
SNN	0.9995	0.9993	0.9991	0.9989	0.9986
Proposed	**0.9997**	**0.9994**	**0.9991**	**0.9989**	**0.9987**

Table 4: IQI values for standard images for the proposed method.

σ	10	20	30	40	50
LENA	0.9951	0.9892	0.9817	0.9730	0.9646

BARBARA	0.9937	0.9880	0.9814	0.9735	0.9645
ZELDA	0.9956	0.9899	0.9835	0.9752	0.9641

6. Results

Selection of bior6.8 wavelet in wavelet denoising stage while denoising the method noise image show improvement in PSNR value as compared to the performance of other wavelets. PSNR value increase up to 0.32 at $\sigma = 10$, by 0.13 for $\sigma = 20$ and 0.04 for $\sigma = 30$ compared to highest PSNR value of the wavelet listed in Table 1. However, for $\sigma > 30$, it remains almost the same or reduces slightly.

The proposed denoising method (SNNMNT) shows an improvement in PSNR value when tested for three different standard images as compared to other denoising methods. PSNR value increase up to 0.94 at $\sigma = 10$, by 0.46 for $\sigma = 20$ and 0.40 for $\sigma = 30$ compared to highest PSNR values of other denoising methods listed in Table 2. However, for $\sigma > 30$, PSNR remains almost the same or reduces slightly.

SSIM parameter measured for the denoised image of LENA, with different filters, shows that the proposed filter has a slightly higher SSIM value (variations at the fourth decimal digit) when tested for noise standards varying from 10 to 50 as referred in Table 3.

7. Conclusion

The Statistical Nearest Neighbor with Method Noise Thresholding (SNNMNT) is proposed in this work. Simulation and executed results show that resultant images have improved performance parameters such as PSNR and SSIN as compared to other denoising techniques. Designing of well-performing prefilter may further enhance the image parameters intern image quality. The proposed filter suffers to maintain image parameters well in all the cases of standard deviation. So one can modify the existing filter to sustain PSNR values. The resultant images through a novel filter have clear edges and smoothen the image.

Simulation results of the present method depict that the denoised image has improved PSNR and SSIM values when compared with other method noise thresholding techniques. The proposed work is best suited for images with high noise and high contrast. Fine-tuning at the pre-filtering stage may further enhance the quality of the image. Implementation of other denoising techniques using the method noise thresholding may result in an improved denoised image. PSNR value substantially reduces for higher noise levels ($\sigma > 30$). There is scope for refinement of image parameters through improved filtering methods for higher σ values. Further, the obtained denoised images through a novel filtering technique have fewer artifacts and are efficient at higher noise levels.

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