

Bio-Medical Image Denoising using Wavelet Transform

L. M. Satapathy, P. Das, A. Shatapathy, A. K. Patel

Abstract: Now a day's images are used in various medical science applications. A good quality image is highly required for proper diagnosis. This paper proposes a novel hybridization technique is proposed to improve the image quality of degraded image by the noise. The decomposition based proposed method initially separates the image into four parts as LL, LH, HL and HH. The high frequency information of the decomposed image is de-noised using the conventional denoising techniques. The resultant image is reconstructed by applying the inverse wavelet transform. In this process the coefficients of the wavelet preserves the useful information corresponding to the image structure, while suppresses the noisy elements. Experiments were conducted on various medical images available in public domain to compare the performance of the proposed algorithm with respect to the conventional methods such as Wiener filter, Median filter and wavelet soft threshold. The validity of the presented approach is subjectively quantified in terms of PSNR, MSE and structural similarity. The experimental results demonstrate that the proposed algorithm outperforms the existing denoising methods. For medical images, the PSNR and the SSIM values improve by using the proposed technique over various denoising approaches.

Index Terms: DWT, IDWT, Image de noising, medical images, ssim .

I. INTRODUCTION

Image denoising is a quality enhancement method in image processing, where the noise is removed from the noisy image and recovers the original image by retaining its quality, which gets corrupted during its acquisition or transmission [1]. In medical field MRI, CT scan, ultrasound, x-ray etc. instruments are used for image acquisition in which noise can be generated [2]. When noise is present in image degrades the objective quality and lowers down the clarity of low contrast object [3]. Denoising is important in medical imaging operations to recover the anatomical details that may be suppressed in the data due to the noise [4]. Bio-medical images are normally - corrupted with noise; which degrade

the useful detail of medical images which may affect the diagnosis. As edges is most essential aspect for bio-medical images, therefore the denoising needs to be balanced with edge preservation. The main problem in bio-medical imaging system is the adoption of the images obtained due to imperfect addition and communication errors. Thus, all medical imaging devices need denoising technique to enhance the image quality which will help the doctors and medical experts for proper diagnosis. Traditional denoising techniques such as Wiener filter, Median filter and wavelet soft threshold are directly applied over noisy image for improving the quality of the image. The Wiener filter was proposed by Norbert Wiener which minimizes the mean square error by computing the statistical estimate of an unknown signal using random process. Due to wiener filter is dynamic and linear it provides point estimation, whereas it has a limitation to remove the multiplicative noise. The Median Filter is a non-linear, edge preservative digital filtering technique widely used in the application field of image processing to remove the noise. The main disadvantage in median filter is its high computational complexity. In recent years, in the field of image denoising domain wavelet transform plays a vital role. Wavelet transform are used as they have localization benefits in space domain and frequency domain. The packets of wavelet allows flexible attainment for a given 2D signal. Many methods are available for denoising of noisy images, but they have complexity in their methods as they are limited to some extent. Traditional methods only de-noise the whole image but it cannot de-noise the low frequency & high frequency component separately due to which the images are changed abruptly. To overcome this problem, the high frequency component of the noisy image is filtered, and the low frequency information is preserved. This motivated us to apply discrete wavelet transform (DWT) based decomposition to the image and as a result the low frequency as well as high frequency components are extracted and then de-noise the high frequency component using traditional denoising filters. The remaining part of this paper is organized as follows: Section 2 provides a brief review of the methodology. Section 3 demonstrated the detail experimental results of the proposed algorithm, and the final conclusions are given in Section 4.

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II. METHODOLOGY

The proposed algorithm gives a brief idea about decomposition-based image de-noising, where initially the noisy image(I) is decomposes into low frequency component as well as high-frequency components using discrete wavelet transform (DWT).

The low frequency component contains the detail information of the image whereas the high-frequency components of the digital image contains the approximation information [5]. The noise generally corrupts the high frequency components; as a result, the image degrades and provides a wrong conclusion. The Fig.1 demonstrates the block representation of the DWT based decomposition method of a noisy image. In Fig.2 the results of the DWT based decomposition is shown and. Fig.3 describes the spectral distribution of the low frequency and high-frequency information of LL, LH, HL and HH.

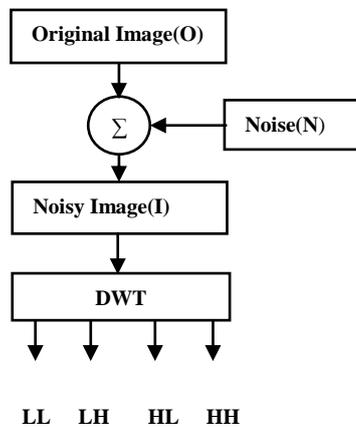


Figure 1. Noisy Image decomposition using DWT.

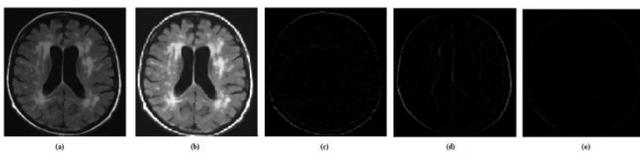


Figure 2. (a) Original image (b) Decomposition of image Low-Low (c) Low-High (d) High-Low (e) High-High.

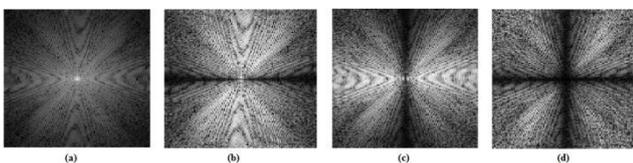


Figure 3. Spectrum of (a) Low-Low (b) Low-High (c) High-Low (d) High-High.

To de-noise the noisy image the conventional denoising technique is applied to the HH. When the HH is processed through the conventional filter HH₁ is produced. The new or de-noised image is generated by applying Inverse discrete wavelet transform (IDWT) to LL, LH, HL and HH₁[6]. The proposed algorithm highlights that conventional filters when

applied with DWT performs better as compare to the direct application of the conventional technique.

A. Discrete wavelet transform

The discrete wavelet transforms (DWT) [5] is an effective and useful tool for decomposing the 2D signal. It provides the time and frequency domain representation. The development of discrete wavelet (DWT) was to overcome the short coming of the Short time Fourier transform (STFT), the use of that to analyses non-stationary signals. A set of mutually orthogonal wavelet basis functions are generated when the Discrete wavelet transform (DWT) decomposes a given signal. The discrete wavelet transform is invertible, so that the original image can be recovered from its discrete wavelet transform (DWT) representation.

B. Noises.

Noise is an unacceptable signal that changes the property and performance of the signal. Normally images are corrupted with noise likely Gaussian, Salt & pepper and speckle distribution.

1) Gaussian noise

Gaussian noise is arising in electronic components which is normally known as electronic noise. It is the demographical noise to that of the original distribution. The noise is independent of each pixel as well as signal intensity and is preservative in nature [7].

The probability density function ‘g’ of a Gaussian random variable ‘u’ is given by:

$$g(u) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(u-\mu)^2}{2\sigma^2}} \tag{1}$$

Where:

- u: Grey level
- μ : Mean or average value
- σ: Standard deviation

2) Salt & Pepper Noise

The other name of salt & pepper noise is impulsive noise[8]. It is generated during sharp and sudden disturbances in the image and represents as white and black pixels. Median filter is mainly used for the noise removal of this type of noises.

The probability density function ‘S’ of a Gaussian random variable ‘u’ is given by:

$$S(u) = \begin{cases} s_p \text{ for } u = 0 \text{ (pepper)} \\ s_s \text{ for } u = 2^n - 1 \text{ (salt)} \\ 1 - (s_p + s_s) \text{ for } u = k \text{ (} 0 < k < 2^n - 1 \text{)} \end{cases} \tag{2}$$

3) Speckle Noise

Another type of noise which corrupts the quality of the active radar, medical images and optical coherence tomography images is known as speckle noise [9].

The major cause of speckle noise generation is the effect of environmental conditions during imaging sensor in the process of image transmission.



Speckle noise follows gamma distribution which is shown below:

$$F(u) = \frac{u^{\alpha-1}}{(\alpha-1)!a^\alpha} e^{-\frac{u}{a}} \quad (3)$$

Where:

- u: Grey level
- a^α : Variance

C. Filters.

In the recent years the big challenge for the researcher to de-noise the image to recover the existing image which was corrupted or blurred. It is necessary step used before the image detail is analyzed. It is important to use a better denoising method to recover the image from the data corruption.

1) Median Filter

Median filter is a nonlinear filter which is used for denoising the image [10]. It works efficiently for removal of salt & pepper noise. The objective of filtering in digital image is denoising as well as edge preservation.

2) Wiener Filter

A Wiener filter which is a flexible low-pass filter uses pixel wise adoption. This is an adaptive filtering method with linear in nature [11]. The method used in wiener filter is a statistics approximation-based approach from nearer of each pixel. The main advantage of this filter is that it preserves the edges of an image.

The Wiener filter is:

$$w(a, b) = \frac{k^*(a,b) P_s(a,b)}{|k(a,b)|^2 P_s(a,b) + P_n(a,b)} \quad (4)$$

Dividing through by P_s makes its behaviour easier to explain:

$$w(a, b) = \frac{k^*(a,b)}{|k(a,b)|^2 + \frac{P_n(a,b)}{P_s(a,b)}} \quad (5)$$

where,

- $k(a, b)$ = Degradation function
- $k^*(a, b)$ = Complex conjugate of degradation function
- $P_n(a, b)$ = Power Spectral Density of Noise
- $P_s(a, b)$ = Power Spectral Density of un-degraded image

3) Wavelet Soft Thresholding

Soft thresholding is a delete and scaling method where the coefficients less than the threshold are deleted and scales that which are left[12]. It is also known as wavelet shrinkage. In comparison to hard thresholding which keeps or removes values of coefficients. The formula for the universal threshold is expressed as follows:

$$\lambda = \sigma \sqrt{2 \ln(M)} \quad (6)$$

Where,

- σ : Average variance of the noise
- M: Signal length

σ is calculated using median estimate method as follows:

$$\sigma = \frac{\text{Median}(|W_{1,K}|)}{0.6745} \quad (7)$$

Soft thresholding function is defined as:

$$\widehat{W}_{j,k} = \begin{cases} \text{sgn}(W_{j,k})(|W_{j,k}| - \lambda); & |W_{j,k}| \geq \lambda \\ 0; & |W_{j,k}| < \lambda \end{cases}$$

III. EXPERIMENTAL RESULTS

3.1 Performance evaluation measure

The proposed algorithm is verified using subjective analysis approach. The performance evaluator such as SSIM, PSNR and MSE are considered to quantify the result.

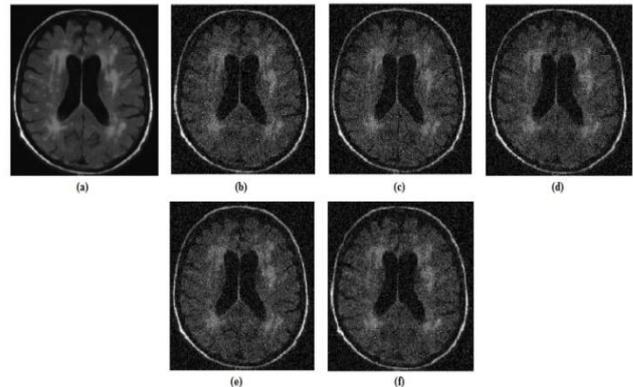


Figure 4. Performance of MRI brain images (a) Input image (b) Noisy image (Gaussian noise with variance 0.01) (c) applying median filter (d) Applying wiener filter (e) Applying soft threshold (f) Proposed method.

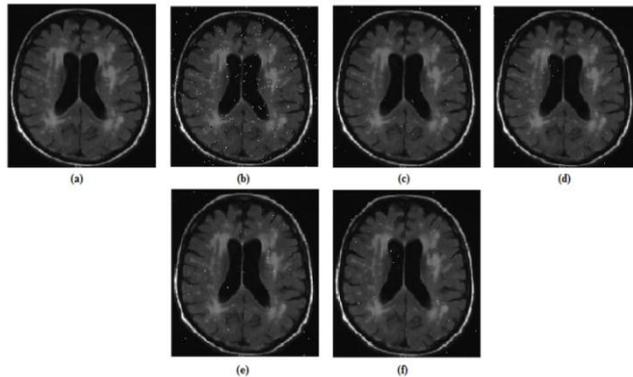


Figure 5. Performance of MRI brain images (a) Input image (b) Noisy image (Salt & Pepper noise) (c) applying median filter (d) Applying wiener filter (e) Applying soft threshold (f) Proposed method.

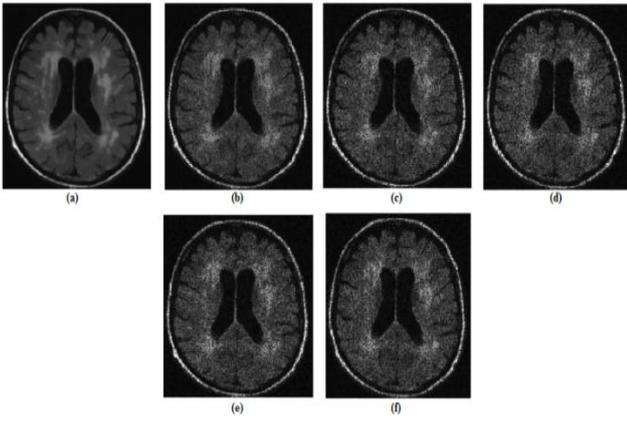


Figure 6. Performance of MRI brain images (a) Input image (b) Noisy image (Speckle noise) (c) applying median filter (d) Applying wiener filter (e) Applying soft threshold (f) Proposed method.

Figure 7. Histogram of MRI brain images (a) Input image (b) Noisy image (Gaussian noise with variance 0.01) (c) applying median filter (d) Applying wiener filter (e) Applying soft threshold (f) Proposed method.

a) Structural Similarity Index (SSIM):

Structural Similarity Index (SSIM) is a perceptual metric that quantifies image quality degradation which is caused by processing such as data compression or by losses in data transmission. It is used for measuring the similarities between two images. It is a full reference metric i.e. the measurement of quality of image is based on an initial uncompressed or distortion free image as reference. SSIM quality assessment index is based on the computation of three terms, namely the luminance term, the contrast term and the structural term. The overall index is a multiplicative combination of the three terms[14].

$$SSIM(a, b) = [q(a, b)]^\alpha [w(a, b)]^\beta [e(a, b)]^\gamma$$

Where $q(a, b) = \frac{2\mu_a\mu_b + C_1}{\mu_a^2 + \mu_b^2 + C_1}$ (8)

$$w(a, b) = \frac{2\delta_a\delta_b + C_2}{\delta_a^2 + \delta_b^2 + C_2}$$
 (9)

$$e(a, b) = \frac{\delta_{ab} + C_3}{\delta_a\delta_b + C_3}$$
 (10)

Where μ_a : Local mean for image a.
 μ_b : Local mean for image b.
 δ_a : Standard deviation for image a.
 δ_b : Standard deviation for image b.

δ_{ab} : cross-covariance for images a, b.

If $\alpha = \beta = \gamma = 1$ and $C_3 = C_2/2$ then the above index is simplifying to:

$$SSIM(a,b) = \frac{(2\mu_a\mu_b + C_1)(2\delta_a\delta_b + C_2)}{(\mu_a^2 + \mu_b^2 + C_1)(\delta_a^2 + \delta_b^2 + C_2)}$$
 (11)

b) Peak signal to noise ratio(PSNR)

PSNR [13] is the ratio between the maximum possible power of a signal and the power of corrupting noise. PSNR measures the peak signal to noise ratio between two images which is used as quality measurement between two images (i.e. original image and compressed image). Higher the value of PSNR, better the quality of the compressed image. PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is calculated as:

$$PSNR_{dB} = 10 \log_{10}\left(\frac{MAX^2}{MSE}\right)$$
 (12)

$$= 20 \log_{10}(MAX) - 10 \log_{10}(MSE)$$
 (13)

Where,

MAX: Maximum possible pixel value of the image.

MSE: Mean Square Error [13].

c) Mean square error(MSE)

The Mean Square Error(MSE) [13] is the cumulative error between the compressed image and the original image. The lower the MSE, better the quality of the compressed image. It is calculated as:

$$MSE = \frac{1}{pq} \sum_{a=0}^{p-1} \sum_{b=0}^{q-1} [I(a, b) - K(a, b)]^2$$
 (14)

Where p, q : Dimension of the image.

$I(a, b)$: Intensity of pixels (a, b) in original image.

$K(a, b)$: Intensity of pixels (a, b) in de-noised image.

3.2. Experimental Results

To validate the proposed algorithm the experiment was conducted and recorded over 30 different images. These images are selected from the open source. To quantify the result average performance of subjective parameters such as PSNR, MSE and SSIM are calculated. The results were compared with state of art traditional de-noising methods. Fig. 4, 5 and 6 demonstrates the behaviors of different noises as Gaussian noise, Salt & Pepper noise, Speckle noise on an image. Then the traditional techniques as (a) median filter (b) wiener filter and (c) soft threshold applied and results are incorporated for visual analysis purpose. Results of proposed algorithm are shown in fig.4-6 and for better comparison Fig.7. is added where histogram distribution of all the methods as well as original image are demonstrated.

The proposed method gives better distribution and avoids the stretching problems. It also preserves the brightness of the image.



Higher value of PSNR in the proposed method concludes that the conventional method with DWT performs better noise reduction [Fig.8]. The mean square error of Fig.9 shows that the proposed method has less error as compare to the other methods. The structural similarity index demonstrates the quality of the de-noised image. Fig.10 indicates that the SSIM of the DWT based noise reduction methods are higher as compare to the conventional methods.

The experiments are also conducted over different images corrupted by Salt & Pepper noise and Speckle noise to validate the proposed algorithm. It was found that the method outperforms on the case of the above-mentioned noise and the evidence is demonstrated in fig.11-13. In the case of PSNR it was evidence that the wiener filter with DWT performs better in the case of Salt & Pepper noise and Speckle noise where as Median filter with DWT gives better result in the case of Speckle noise. In the case of MSE it was found that the proposed method has low values as compared to the traditional methods [Fig.12].

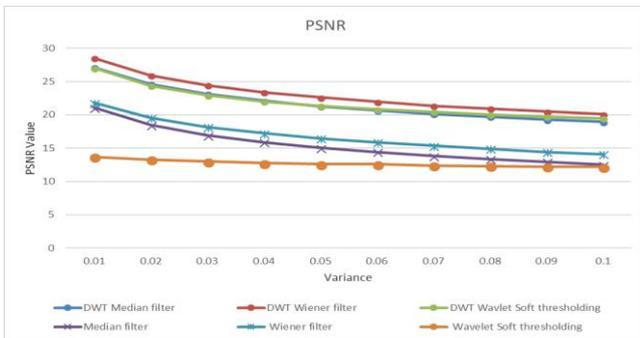


Figure 8. PSNR comparison of variances using different denoising schemes for Gaussian noise.

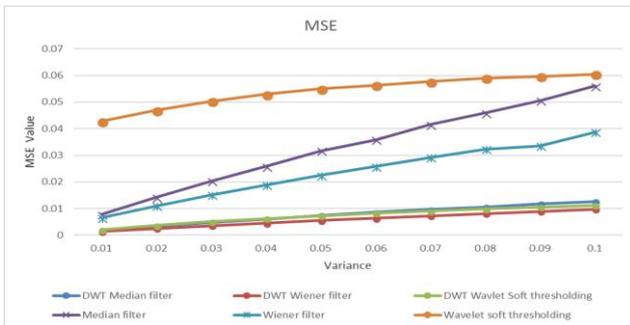


Figure 9. MSE comparison of variances using different denoising schemes for Gaussian noise.

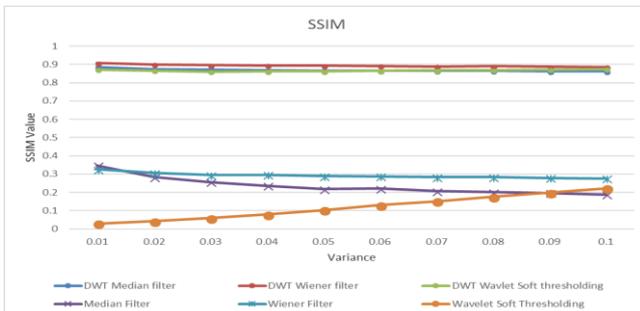


Figure 10. SSIM comparison of variances using different denoising schemes for Gaussian noise.

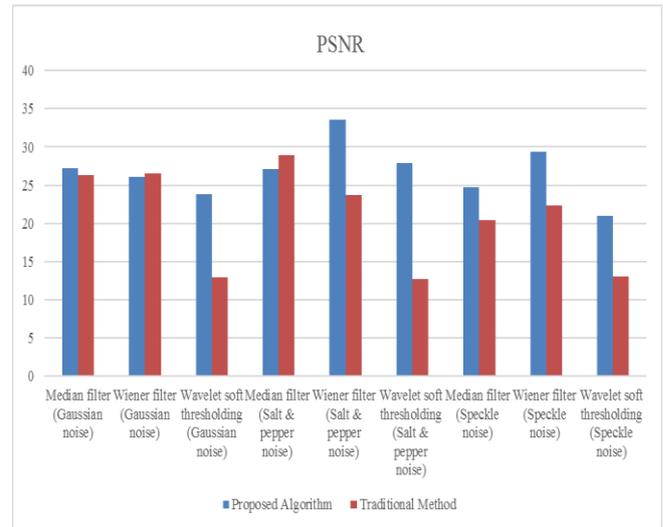


Figure 11. PSNR comparison of proposed algorithm & traditional method using various denoising schemes for different type of noises.

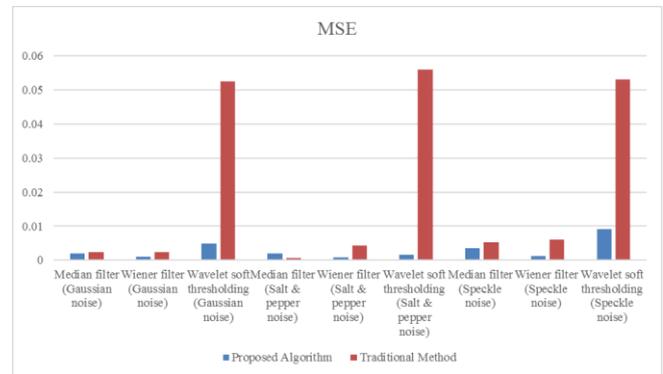


Figure 12. MSE comparison of proposed algorithm & traditional method using various denoising schemes for different type of noises.

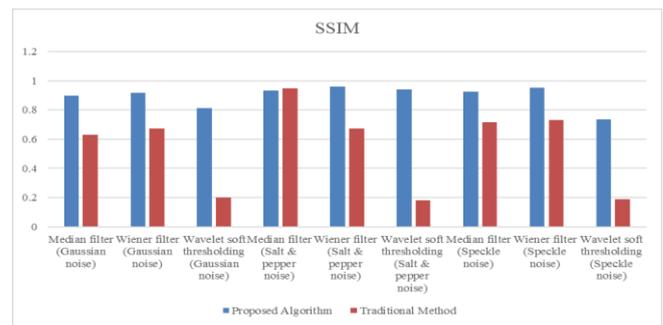


Figure 13. SSIM comparison of proposed algorithm & traditional method using various denoising schemes for different type of noises.

The SSIM of the proposed method evidence that the denoising with DWT method has high similarity value to the original image.

IV. CONCLUSION

The wavelet-based hybrid denoising method is introduced in this paper. This method is implemented and tested on number of images available publicly.

The main objective behind the proposed method is to decompose the image before denoising. Only the high frequency information is de-noised using traditional methods and the low frequency information are preserved to recovery the original image. In this method, the image quality is improved in terms of detail and edge, and the noise was removed. Using traditional denoising methods with the decomposition technique gives better result as compare to the traditional methods only. The proposed algorithm concludes that the method has better denoising effect on medical images.

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