Medical Image De-Noising using Wavelet Transform

Jagdeep Kaur[1] Ruchika Manchanda[2]
[1,2]Department of Electronics & Communication Engineering
[1,2]Guru Nanak Institute of Technology, Mullana, India

Abstract— The goal of de-noising method in Wavelet de-noising removes the noise present in the image while preserving the image characteristics regardless of its frequency content. Wavelets preserve visual quality and also maintain the diagnostically significant details of medical images. The purpose of de-noising is to remove the noise while retaining the edges and other detailed features as much as possible. In this paper a wavelet based denoising technique is evaluated by implementing the improved algorithm on medical images with simulated noise. To conclude standard parameters like MSE and PSNR are used for image evaluation.

Key words: Medical Image De-Noising, Wavelet Transform

I. Introduction

Technological developments in X-Rays, ultrasound, magnetic resonance imaging and other imaging techniques have produced a non-invasive method for diagnosis. A number of new techniques have also flourished, making use of latest technology for better imaging. Imaging can provide uniquely valuable information about physical and structural properties of organs, as well as quantitative descriptions of many fundamental biological processes. There are many advanced methods ofimage processing involving techniques that include the traditional Fourier transform and the wavelet transform [1]. Recently there exist a variety of wavelet transform based methods developed with added advantages over classical methods, these include shift invariance [2] and improved texture conservation. The de-noising algorithms apply a chosen method of wavelet decomposition for the reconstruction of medical images [4] The image-processing process amplifies part of the noise and adds its own rounding noise. Rounding noise occurs because there are only a finite number of bits to represent the intermediate floating point results during computations. Most de-noising algorithms assume zero mean additive white Gaussian noise (AWGN) because it is symmetric, continuous, and has a smooth density distribution [11]. Researchers published different ways to compute the parameters forthe thresholding of wavelet coefficients. Data adaptive thresholds [6] were introduced to achieve optimumvalue of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on Thresholding of an Un-decimated Wavelet Transform [3] These thresholding techniques were applied to the non-orthogonal wavelet coefficients to reduce artifacts. Multi-wavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to out perform the thresholding techniques and gained ground. Recently, much effort has been devoted to Bayesian de-noising in Wavelet domain [13]. The performance of the de-noising algorithms is quantitatively assessed using different criteria namely the PSNR, MSE and the visual appearance. Two commonly used measures are Mean-Squared Error and Peak Signal-to-Noise Ratio[15]. Wavelet based de-noising has opened up other fields and important techniques such as denoising and non-linear approximation, smoothing and restoration of images. The goal of image de-noising is to remove noise by differentiating it from the signal. The wavelet transform's energy compactness helps greatly in de-noising. The Discrete Wavelet Transform (DWT) is a powerful tool for multi resolution decomposition of image.

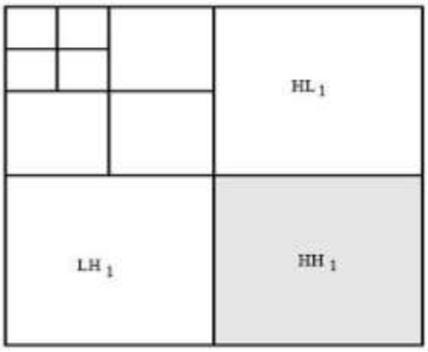


Fig. 1: Wavelet Decomposition Tree

The wavelet decomposition of an image is done as follows: In the first level of decomposition, the image is split into four sub bands, namely HH1, HL1, LH1, and LL1, as illustrated in Figure 1. The HH1 sub-band gives the diagonal details of the image; the HL1 sub band gives the horizontal features, while the LH1 represents the vertical structures. The LL1subband is the low resolution residual consisting of low frequency components and it is this sub band which is further split at higher levels of decomposition. It has been shown that the noise standard deviation ¾w can be accurately estimated from the first decomposition level diagonal sub band HH1 by the robust and accurate median estimator [4], as given by

$$\sigma_w = \frac{median(|HH_1|)}{0.6745} \qquad (1)$$

The choice of wavelet is dictated by the signal or image characteristics and the nature of the application.

II. Methodology

Standard medical images are taken for the process to study the performance of the algorithm. A noise addition code is first written to add noise artificially in original image. The parameter standard deviation for noise is controlled in algorithm. A set of images with varying SD is produced and kept for the test purpose. The simulation of noise is performed to mimic the real conditions of a medical system. Here, we used ultrasound and MRI images for testing of de-noising algorithm. These images are corrupted with uniformly distributed multiplicative noise having different levels of variance of the noise. By taking four different values of noise variances, four different medical noisy images are being obtained. The range of noise variance are [0.1 1], where the variance 0.1 represents low level noisy image and variance 1 represents a high level noisy image.

De-noising can be achieved by applying a thresholding operator to the wavelet coefficients (in the transform domain) followed by reconstruction of the signal to the original image (spatial) domain. Quantitatively assessing the performance in practical image application is complicated issue because the ideal image is normally unknown. Therefore the rational approach is to use known images for the tests, as in other image processing applications, in order to test the performance of the wavelet denoising methods like one dimensional signal denoising. Fig-2 represents the medical test image for testing the algorithm. Here, we use again a classical comparison receipt based on noise simulation.

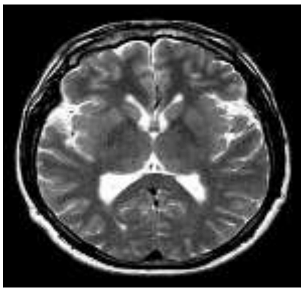
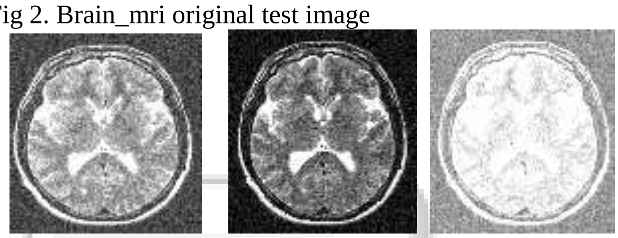


Fig 2. Brain_mri original test image



(a) (b) (c)

Fig- 3: Original image added with artificial noise with variance (a) 0.1 (b) 0.3 and (c) 0.5

The comparison can be realized on the result reconstructed image and the original image after adding Gaussian white noise with known power to the original signal. Then it will be computed the best image recovered from the noisy one for each method.

Typical threshold operators for de-noising include

- Hard Thresholding and
- Soft Thresholding

Hard-thresholding is a type of global thresholding, in this thresholding method thresholds the complete image with a single threshold value. So using that method for image de-noising select one threshold value for whole image. Hard thresholding sets to zero those elements whose absolute value is lower than the threshold value and neglecting zero element. Hard thresholding function is as follows:

$$\rho_T(x) = \begin{cases} x, if & |x| > T \\ 0, if & |x| \le T \end{cases}; \qquad (2)$$

and soft thresholding

$$\rho_T(x) = \begin{cases} x - T, & if \quad x \ge T \\ x + T, & if \quad x \le -T; \\ 0, & if \quad |x| < T \end{cases} \qquad (3)$$

A. *Algorithm for De-Noising using Wavelets*

- Step-1: Take an original image.
- Step-2: Add different variance of noise with original image.
- Step-3: Apply wavelet transform
- Step-4: Adjust threshold and level of decomposition
- Step-5: Apply inverse wavelet transform.
- Step-6: Save the restored image after applying IWT from inverse transform.
- Step-7: Compare the restored image that obtained in step 6 with original image and estimate various statistical parameters like MSE and PSNR, etc.
- Step-8: Repeat the previous steps unless desired level of PSNR and image details are not obtained.

The parameters which are used in the filter performance evaluation are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) [13, 14].

1) *Measurement of MSE*

MSE is define as the average of square of the error. The MSE provides a means of choosing the best estimator. The MSE is defined as:

$$e_{MSE} = \frac{1}{MN} \sum_{n=1}^{M} \sum_{m=1}^{N} [\hat{g}(n,m) - g(n,m)]^2 \qquad (4)$$

2) *Measurement of PSNR*

The Peak Signal-to-Noise Ratio (PSNR) [36] is defined as a ratio between the maximum possible power of a signal and the noise power that affects the fidelity of its representation. PSNR is usually expressed in terms of the logarithmic decibel scale. The PSNR is most commonly used as a measure of quality of reconstruction of lossy compression for image compression.

The PSNR is defined as:

$$PSNR = -10 \log_{10} \frac{e_{MSE}}{S^2} \qquad (5)$$

3) *Visual comparison*

Final performance check is done by a visual inspection of the recovered or de-noised image. The de-noised image is analyzed for getting the texture related details in image.

III. RESULTS & CONCLUSION

Frequency domain image de-noising methods are more efficient as compared to other methods. When using the wavelet transformation for image de-noising there's much flexibility in altering the algorithm parameters. Depending on the noise levels and type of image the algorithm can be optimized to achieve optimum output. Although noise added artificially can only be closely approximated to real life situations, still these provide a set of rules for applying the algorithm.

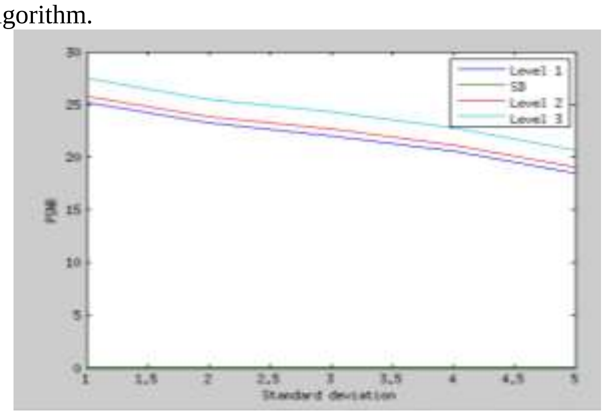


Fig. 4: Graph of standard deviation and PSNR for different levels of decomposition

When applying wavelet parameters varied are the noise level and threshold level K. The analysis are made on the basis of PSNR and MSE values fig.4 and fig.5. Finally a visual inspection of the image is performed to validate the results. The level of thresholding is an important factor to reconstruct the image with more details present in it. With different data sets varying the noise level and other threshold control parameters results were analyzed to find a better visibility and value of PSNR.

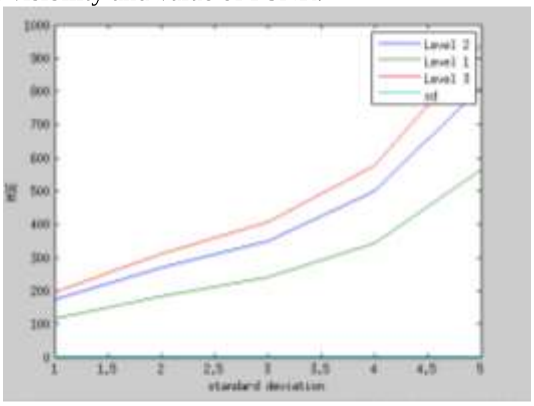
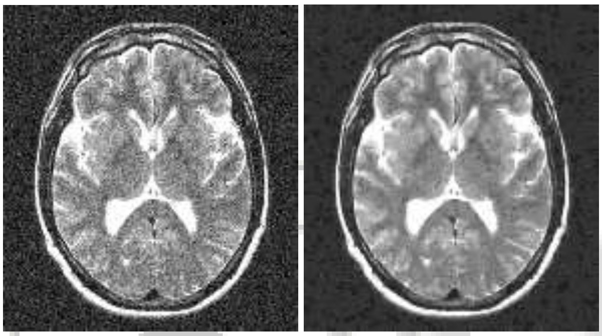
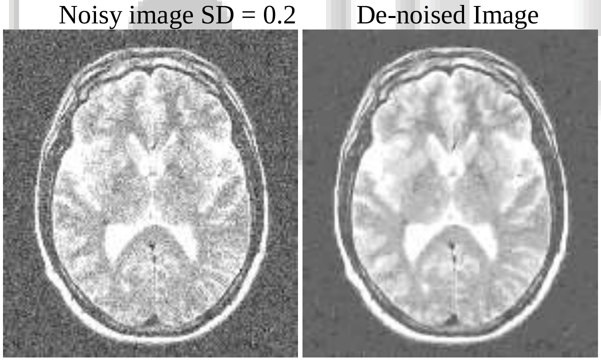


Fig. 5: Graph of MSE with standard deviation

The graphs represent PSNR and MSE of images de-noised using the modified parameters. Some of the input images and the de-noised images applying the algorithm are shown below.



Noisy image SD = 0.2 De-noised Image



Noisy image SD = 0.4 De-noised Image

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