

International Journal of Advance Research in Computer Science and Management Studies

Research Paper

Available online at: www.ijarcsms.com

Performing Various Image Denoising Techniques for Medical Images

B. L. Prakash¹

Professor

Department of ECE

Vignan's Institute of Information Technology

Visakhapatnam - India

Vudimudi Roja Bharathi²

M.Tech Scholar

Department of ECE

Vignan's Institute of Information Technology

Visakhapatnam - India

Abstract: The problem of noise effects on the Medical Images normally degrades its quality and misleading the actual problem in the image. Image denoising vital role in image restoring and enhancement process, use of wavelet transform improves the quality of an image and reduces noise level. In this paper, we proposed novel noise reduction algorithms that can be used to enhance image quality in various medical imaging modalities. The image is decomposed using Haar and Daubechies transforms, and then the level of soft and hard threshold is selected for reducing the noise in the image and after that by calculating and comparing the PSNR of an image for every wavelet

Keywords: Db3, Haar, MSE, PSNR, Threshold.

I. INTRODUCTION

There are different techniques for producing medical images such as Magnetic Resonance Imaging (MRI), X-ray, Computed Tomography and Ultrasound, during this process noise is added that decreases the image quality and image analysis.

The advent of digital imaging technologies such as MRI has revolutionized modern medicine. Today, many patients no longer need to go through invasive and often dangerous procedures to diagnose a wide variety of illnesses. With the widespread use of digital imaging in medicine today, the quality of digital medical images becomes an important issue. To achieve the best possible diagnoses it is important that medical images be sharp, clear, and free of noise and artifacts. While the technologies for acquiring digital medical images continue to improve, resulting in images of higher and higher resolution and quality, noise remains an issue for many medical images. Removing noise in these digital images remains one of the major challenges in the study of medical imaging.

While noise in medical images presents a problem because they could mask and blur important but subtle features in the images, many proposed denoising techniques have their own problems. One of the widely discussed techniques is the wavelet Thresholding scheme, which recognizes that by performing a wavelet transform of a noisy image, random noise will be represented principally as small coefficients in the high frequencies.

Thus in theory a Thresholding, by setting these small coefficients to zero, will eliminate much of the noise in the image. The wavelet hard Thresholding scheme, which sets wavelet coefficients below certain threshold in magnitude to 0, easy to implement and fast to perform. And depending on the threshold it removes noise adequately. However, at the same time it also introduces artifacts as a result of the Gibbs oscillation near discontinuities. Since artifacts in medical images may lead to wrong diagnoses, the wavelet hard Thresholding scheme is not practical for use in medical imaging without being combined with other techniques. An improvement over the wavelet hard Thresholding is the wavelet soft Thresholding scheme [3, 5], which significantly reduces the Gibbs oscillation but does not eliminate it. The effectiveness of wavelet thresholding schemes in general is limited with combining them with other techniques. This other more complex techniques often try to take account of

geometric information's by using wavelet-like bases that better characterize discontinuities, such as curvelets [2, 3]. Nevertheless, they do not completely eliminate the Gibbs phenomenon. Other methods with varying success have also been studied by different authors,[1]

Another approach employs variational principles and PDE based techniques. In this approach, a noisy image is modeled as $z(x) = u_0(x) + n(x)$ where u_0 denotes the uncontaminated underlying image and n denotes the noise. To reconstruct u_0 one considers the problem of minimizing

$$E(u) = \frac{\lambda}{2} \|u - z\|_{L^2(\Omega)}^2 + R(u), \quad (1)$$

Where $\lambda > 0$, Ω is the domain on which z is defined, and the term $R(u)$ is a regularization functional. Earlier efforts focused on least square based functional $R(u)$'s. While noise can be effectively removed, this regularization functional penalizes discontinuity, resulting in soft and smooth reconstructed images, with subtle details lost. Eq(1) Again, for medical imaging this is not practical, as subtle details could very well yield crucial information about the patients.

A better choice for $R(u)$ was proposed in [25], in which $R(u)$ is the total variation (TV) of u given by

$$R(u) = TV(u) := \int_{\Omega} |\nabla u| dx. \quad (2)$$

Intensive studies have shown that the total variation better preserves edges in u , thus it allows for sharper reconstructions. Among all the PDE based techniques, the wavelet based method is a one method of denoising that offers the best combination of noise removal and feature preservation eq(2).

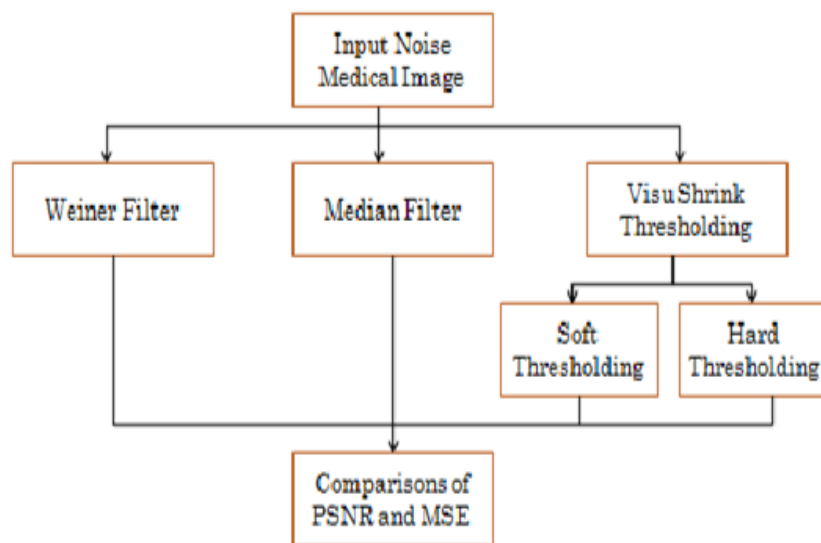


Fig. 1: Block Diagram of medical image denoising

II. THRESHOLDING

2.1 Introduction

The plot of wavelet coefficients in Fig 1 suggests that small coefficients are dominated by noise, while coefficients with a large absolute value carry more signal information than noise. Replacing noisy coefficients (small coefficients below a certain threshold value) by zero and an inverse wavelet transform may lead to a reconstruction that has lesser noise.

2.2 Hard and soft thresholding

Hard and soft thresholding with threshold, are defined as follows:

The hard thresholding operator is defined as:

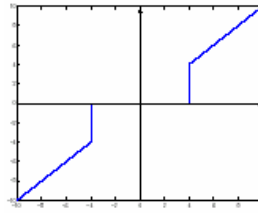


Fig. 2: Hard Thresholding

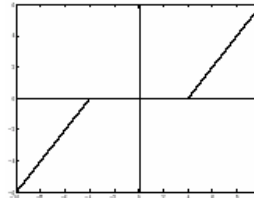


Fig. 3: Soft Thresholding

Hard threshold is a “keep or kill” procedure and is more intuitively appealing. The transfer function of the same is shown in Fig 2.

The alternative, soft thresholding (whose transfer function is shown in Fig3), shrinks coefficients above the threshold in absolute value. While at first sight hard thresholding may seem to be natural, the continuity of soft thresholding has some advantages. It makes algorithms mathematically more tractable. Moreover, hard thresholding does not even work with some algorithms such as the GCV procedure. Sometimes, pure noise coefficients may pass the hard threshold and appear as annoying ‘blips’ in the output. Soft thresholding shrinks these false structures.[1]

2.3 Threshold selection

As one may observe, threshold selection is an important question when denoising. A small threshold may yield a result close to the input, but the result may still be noisy. A large threshold on the other hand, produces a signal with a large number of zero coefficients. This leads to a smooth signal.

Paying too much attention to smoothness, however, destroys details and in image processing may cause blur and artifacts.

The setup is as follows:

- i. The original signals have length 2048.
- ii. We step through the thresholds from 0 to 5 with steps of 0.2 and at each step denoise the four noisy signals by both hard and soft thresholding with that threshold.
- iii. For each threshold, the PSNR and MSE of the denoised signal is calculated.
- iv. Repeat the above steps for different orthogonal bases, namely, Haar, Daubechies.

III. RESULTS

The experimental evaluation is performed on three grey scale images 256×256 pixels at different noise levels. The wavelet transform employs Daubechies’s least asymmetric compactly supported wavelet with eight vanishing moments at five levels of decomposition. The objective quality of the reconstructed image is measured by:

$$PSNR = 10 \log_{10} \frac{255^2}{mse} \text{ dB} \quad (3)$$

Where mse is the mean square error between the original and the denoised image with size I×J:

$$mse = \frac{1}{I \times J} \sum_{i=1}^I \sum_{j=1}^J [x(i, j) - x(i, \hat{j})]^2 \quad (4)$$

Here the original image is corrupted with noise and then the image is recovered. MSE between the original image and enhanced image is calculated and is used in the calculation of PSNR. Thus enhancement in image quality is quantified using values of PSNR calculated for all output images enhanced through different algorithms.

These images considered with Gaussian noise and their denoised images evolved with different filtering techniques. And PSNR and MSE are calculated with respect to denoised image and the original image by using the eq(3) and eq(4).





IMAGES	WEINER		MEDIAN		VISUSHRINK			
					HARD THRESHOLD		SOFT THRESHOLD	
	MSE	PSNR	MSE	PSNR	MSE	PSNR	MSE	PSNR
	980	13.903	930	14.407	879.52	15.758	588.3	17.504
	910	17.546	843	18.932	751.86	19.703	538.9	21.149
	790	20.499	657	21.112	590.71	24.955	456.5	26.074
	810	15.186	722	16.123	638.76	17.747	470.7	19.073

Table: PSNR and MSE of the different images are calculated when they are undergo with different filtering techniques.

IV. CONCLUSION

A variety of survey has been done in this paper. We have discussed various denoising algorithms. A literature survey for various images denoising process was done. Proposed method can provide better results in terms of image quality and calculated the amount of noise added to the pixel, removal of noise and evaluating the peak signal to noise ratio. Thresholding techniques used with Multi - wavelet are simplest to implement.

V. FUTURE SCOPE

The above calculations are being performed on an image of resolution and work is being done to remove speckle noise of the images and future plan is to make it valuable for different resolution and for different size of images. Medical images corrupted by other noises like Gaussian or salt & pepper can also be denoised and PSNR values can be enhanced.

References

1. Buades, B. Coll, J.-M. Morel, A non-local algorithm for image denoising, IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Volume 2, 20-25 June 2005.
2. E. Candès and D. Donoho, Curvelets - A Surprisingly Effective Nonadaptive Representation for Objects with Edges, Curves and Surfaces, L. L. Schumaker et al. Eds, Vanderbilt University Press, Nashville, TN. 1999.

3. E. J. Candès, and F. Guo. Edge-preserving Image Reconstruction from Noisy Radon Data, (Invited Special Issue of the Journal of Signal Processing on Image and Video Coding Beyond Standards.), 2001.
4. D. L. Donoho, De-noising by soft-thresholding, IEEE Trans. Information Theory, 41(3):613-627, 1995.
5. T. F. Chan, S. Osher, and J. Shen, The Digital TV Filter and Nonlinear Denoising, IEEE Trans. Image Proc., 10(2), pp. 231-241, 2001.
6. R. Chan, S. Riemenschneider, L. Shen and Z. Shen, Tight Frame: the efficient way for high-resolution image reconstruction. Applied and Computational Harmonic Analysis, 17(1) (2004), pp91-115.
7. D. L. Donoho and I. M. Johnstone, Ideal spacial adaption by wavelet shrinkage. Biometrika, 81:425-455, 1994.
8. L. Rudin, S. Osher and E. Fatemi, Nonlinear Total Variation Based Noise Removal Algorithms, Physica D, Vol 60(1992), pp. 259-268.

AUTHOR(S) PROFILE



Mr. B. L. Prakash obtained his B.Tech Degree from Nagarjuna University, in the year 1988. He obtained his M.E. degree from Andhra University, Visakhapatnam in the year 2003. He became a Life member of I.S.T.E. in the year 1989, Life member of Institute of Engineers in the year 2001 and Life Fellow of I.E.T.E. in the year 2007. Presently working as a Professor in the department of ECE, Vignan's Institute of Information and Technology, Duvvada, affiliated to JNTU Kakinada. He own 11 papers in various National and International conferences and journals. He is the Vice-Chairman of I.E.T.E. Visakhapatnam center.



Ms V. Roja Bharathi obtained her B.Tech (ECE) Degree from Kaushik Engineering College, Visakhapatnam affiliated to JNTU Kakinada in 2007-11. Presently he pursuing her M.Tech (Electronics & Communications Systems) at Vignan's Institute of Information and Technology, Duvvada, affiliated to JNTU Kakinada.