ISSN 2229-5518

Robust Rician Noise Estimation and Filtering for Magnetic Resonance Imaging

Hareni Jagadeesan, Sasirekha.N

Abstract— This paper proposes a novel method for Rician noise in Magnetic Resonance Imaging (MRI). Noise in MRI is predominantly is Rician, which is signal dependent and it severely affects the contrast of the image. Pixelwise S estimate is highly effective for asymmetric distributions which are often encountered in the regions containing edges. UDWT provides effective representation of noisy coefficients. Pixelwise S estimate based wavelet transform combined with Thresholding and Bilateral Filtering provides efficient feature based preservation. The performance metrics both quantitative and qualitative, demonstrate the effectiveness of the proposed method in Rician denoising.

Index Terms—Bilateral Filter, Magnetic Resonance Imaging, Median Absolute Deviation, Pixelwise S Estimate, Rician Distribution, Soft Thresholding, Undecimated Wavelet Transform

1 Introduction

MAGNETIC Resonance Imaging is an effective imaging technique to study the characteristics and functional aspects of internal organs. Noise corrupts the image during acquisition thereby degrading the visual and diagnostic quality. An effective denoising procedure should strongly preserve the boundaries and at the same time remove noise. A tradeoff between blurring of the image and noise removal always exist.

Noise in MRI is Rician distributed [1] and since it is signal dependent, estimation of parameters from Rician data is complex. The MR image is reconstructed by calculating the Inverse Fourier Transform of the raw MR data. The signal component present in both the real and imaginary channels is affected by additive white Gaussian noise. The MRI tends to follow a Rician distribution because it is the sum of two independent Gaussian variables. In regions of low contrast, the Rician distribution tends to a Rayleigh distribution and in regions of high contrast it tends to a Gaussian distribution. In high resolution, low SNR images, Rician noise is very hazardous since it tends to cause random variations which severely affects the contrast of the image. Wavelet domain noise estimation techniques have become very popular in the recent years. Though the discrete wavelet transform is computationally fast the major drawback is that it is not translation variant. Undecimated Wavelet transform (UDWT), as the name suggests does not decimate the signal and hence provides precise localization based on frequency. The maximum information of the image is contained in the approximation subband and the detail subband contains information on edges and noise components. The UDWT concedes all the significant coefficients into the approximation subband. The S estimate is an alternative for median absolute deviation (MAD). MAD takes a symmetric view on dispersion and hence is not effective for asymmetric distributions. Since the information from the variance estimate is necessary to distinguish between flat and transitional regions, a robust estimate for variance with the above characteristic, known as the S-estimate was introduced in [2].

$$S = med_i\{med_j \mid t_i \quad t_j \mid\} \tag{1}$$

But the computational complexity involved in the calculation of S-estimate is very high when the sample size is large. Hence a new estimate was proposed by a pixelwise modification known as the Pixelwise S Estimate (PWS) [3]. If W_K specifies a window of size *(2l+1)* × *(2l+1)* with *K=2l+1* and centered at (0, 0) denoted by,

$$W_K = \{(m,n) \mid \quad l \le (m,n) \le l\square, K = 2l+1\} \tag{2}$$

W_K^0 denotes the same set of coordinates excluding the central coordinate, $W_K^0 = W_K \setminus (0,0)$. The absolute difference between the centre pixel x_{pq} and neighboring pixel $x_{p+m,\, q+n}$, from the window W_K^0, is defined as

$$d_{pq}(m,n) = \mid x_{p+m,q+n} - x_{pq} \mid, (m,n) \square\ W_K^0 \tag{3}$$

The MAD is given by

$$MAD_{pq} = med\{d_{pq} \mid \square (s,t) \square\ W_K^0 \tag{4}$$

Finally, we define the pixel-wise S-estimate as the median value of medians of absolute differences in a window W_K:

$$PWS_{pq} = med\{MAD_{p+m,q+n} \mid \forall (m,n) \in W_K \tag{5}$$

The PWS can be comprehended to give better approximations and at the same time be less susceptible to noise. Bilateral filter developed by Tomasi et al., is a nonlinear filter that preserves the edges. Bilateral filter preserves the edges by selectively choosing which pixels are allowed to contribute to the weighted sum. It replaces the focal pixel with the bilaterally weighted sum of pixels in the neighborhood.

2 Existing Methods

A method to suppress impulse noise in commercial images based on PWS Edge Preserving Regularisation was introduced. This method uses both the PWS and MAD statistics and creates a noise map to classify the pixels as noisy and noise free. The classified noisy pixels are further processed using an edge preserving regularisation filter. Wavelet based denoising schemes that exploit the multiresolution characteristics of the transform have been successfully developed in [4],

ISSN 2229-5518

[5], and [6]. Shyam Anand et.al, has proposed a wavelet domain bilateral filter that is adapted for Rician noise characteristics. Neigh Shrink Thresholding combined with Wavelet domain Bilateral Filter (WDBF) provided better performance characteristics compared to Unbiased Non Local Means Filtering and (UNLM) and WDBF with Soft Thresholding.

Henkelman [7] estimated the magnitude MR image from a noisy image. The article proved that noise influence may tend to overestimate a signal and offered a solution based on the intensity of the image. Bilateral filter is a popular non-linear filter employed in spatial domain for edge preserved denoising [8].Parameter Estimation from Rician distributed MR data using the Maximum Likelihood estimator (ML) was first introduced by Sijbers et.al. [10]. ML estimator is unbiased and works uniformly well for all ranges of SNR. Though the scheme introduced by Weaver et al., was effective in noise removal, it eliminated details which had a similar noise structure thus degrading the diagnostic quality.

Wavelet transform based denoising for Rician noise removal in MRI was proposed by Nowak [11]. The paper proposes a novel wavelet-domain filtering technique that adapts to variations in both signal and noise.

3 METHODOLOGY

The images obtained in real time are in DICOM format. DICOM stands for Digital Imaging and Communications in Medicine, is a comprehensive set of standards for handling, storing and transmitting information in medical imaging. The denoising algorithm is carried out in MATLAB and as a preprocessing step the DICOM format is converted into a standard double precision image. The MRI data is analysed using a three level UDWT which results in approximation and details coefficients. Higher levels of decompositions results in a different gray level distribution than the original image, hence the decomposition level of three is chosen. PWS of all the coefficients in the horizontal, vertical and diagonal subband are estimated. The approximation coefficients in the third level are filtered using bilateral filter. The resultant of Bilateral Filtering is the denoised form of approximation coefficients.
Soft thresholding is applied to the detail coefficients containing the vertical, horizontal and diagonal subbands. Fixing the appropriate threshold is very critical for edge preservation. The inverse UDWT is then computed. The residue is obtained by subtracting the input and the denoised output pixel by pixel.

4 PERFORMANCE METRICS

The efficiency of the denoising methods is verified quantitatively and qualitatively. For quantitative assessment PSNR and SSIM are calculated. These metrics are computed with the noise-free MR image as the ground truth. Visual assessment of the residual image and the contrast measure are employed for qualitative evaluation.

4.1 Peak Signal to Noise Ratio

The peak signal to noise ratio (PSNR) is a commonly used metric and is calculated using the formula given below:

$$(6) \quad PSNR = 20\log_{10}\frac{MAX_f}{\sqrt{\mathrm{MSE}}}$$

where the MSE (Mean Squared Error) is defined as shown :

$$MSE = \frac{1}{xy}\sum_{0}^{m\ \ 1}\sum_{0}^{n\ \ 1}||\,x(i,j)\quad y(i,j)\,||^2 \qquad (7)$$

where
x represents the matrix data of the original image;
y represents the matrix data of the noisy image;
m represents the numbers of rows of pixels of the image;
n represents the number of columns of pixels of the image;
i represents the index of the row;
j represents the index of the column;
MAX_f is the maximum signal value that exists in the original image;

4.2 Structural Similarity Index

The structural similarity (SSIM) index measures the similarity between two images in a manner that is more consistent with human perception than traditional techniques like mean square error (MSE). The final value of SSIM is the mean of the SSIM index calculated over the N local regions. The SSIM between the images X and Y is evaluated from

$$SSIM(x,y)_N = \frac{(2\mu_x\mu_y + c_1)}{(\mu_x^2 + \mu_y^2 + c_1)}\frac{(2\sigma_{xy} + c_2)}{\sigma_x^2 + \sigma_y^2 + c_{12}} \qquad (8)$$

where μ is the mean intensity, σ denotes the standard deviation and c_1 and c_2 are constants. Therefore, the mean value of SSIM index is:

$$SSIM(X,Y) = \frac{1}{N}\sum_{R=1}^{N} SSIM(x,y)_R \qquad (9)$$

5 RESULTS AND DISCUSSIONS

To demonstrate the efficiency of the proposed method, data obtained using a 1.5T Philips MRI scanner is used. Performance metrics like the PSNR and SSIM are computed. Fig. 1 shows the original clinical image and Fig.2 represents the image corrupted by noise. It is evident from Fig.2 that the Rician noise affects the contrast of the image. The UDWT coefficients are shown in Fig. 3. Fig.4 shows the PWS of the horizontal, vertical and diagonal details of all the three levels. Fig. 5 shows the Filtering and Thresholding operation. Fig. 6 shows the denoised image obtained as the result of the algorithm applied. The structural details have been preserved and the filtered image has an output PSNR of 26.9097 dB. The residue obtained is shown in Fig. 7. From the obtained results we can conclude that for an input noisy image with a PSNR of 24.7984 dB, the algorithm improved the PSNR to 26.9097 dB. Fig. 8 shows how the output PSNR varies as the image is corrupted by Rician noise of varying levels (denoted in percentage). The SSIM shows the structural and the perceptual closeness between the denoised and original image.

ISSN 2229-5518

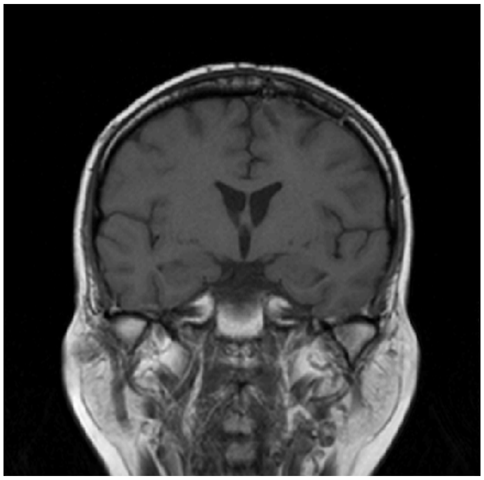

Figure 1: Original Clinical Image and Noisy Image

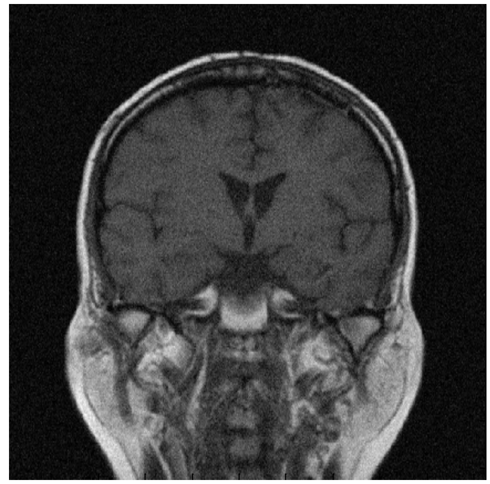

Figure 2 : Reconstructed Noisy Image based on PWS

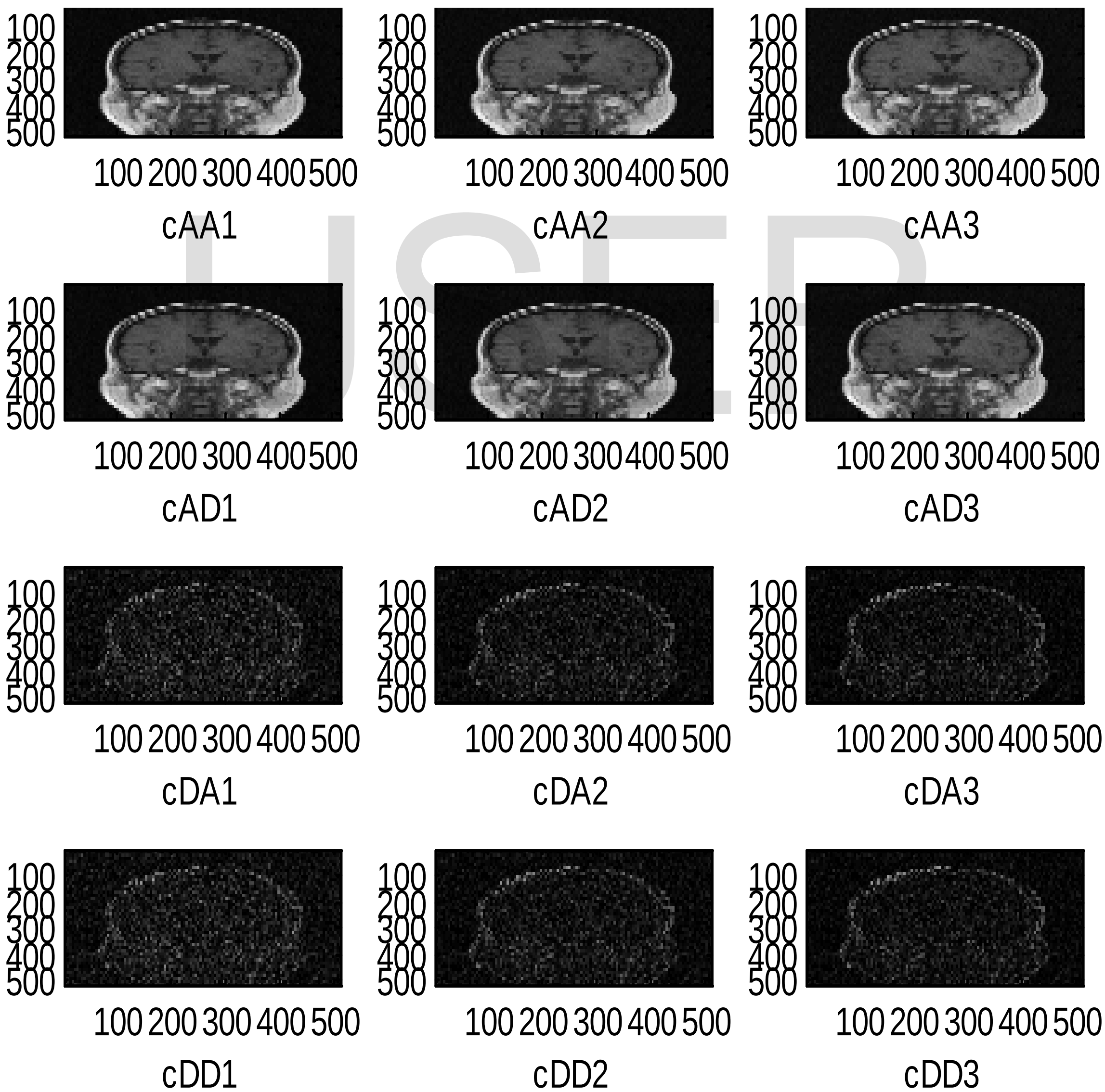

Figure 3: Wavelet Decompostion of the Noisy Input Image

ISSN 2229-5518

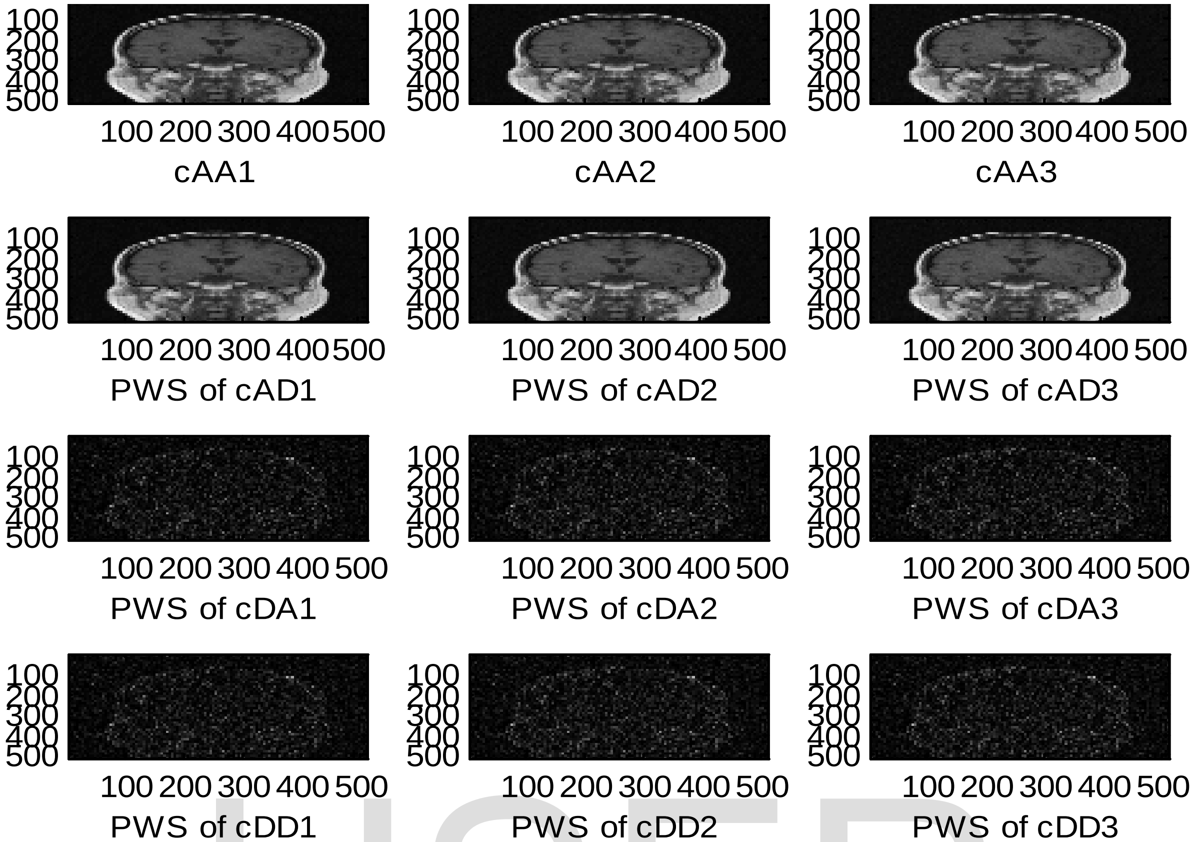

Figure 4: PWS of the Horizontal, Vertical and Diagonal Details

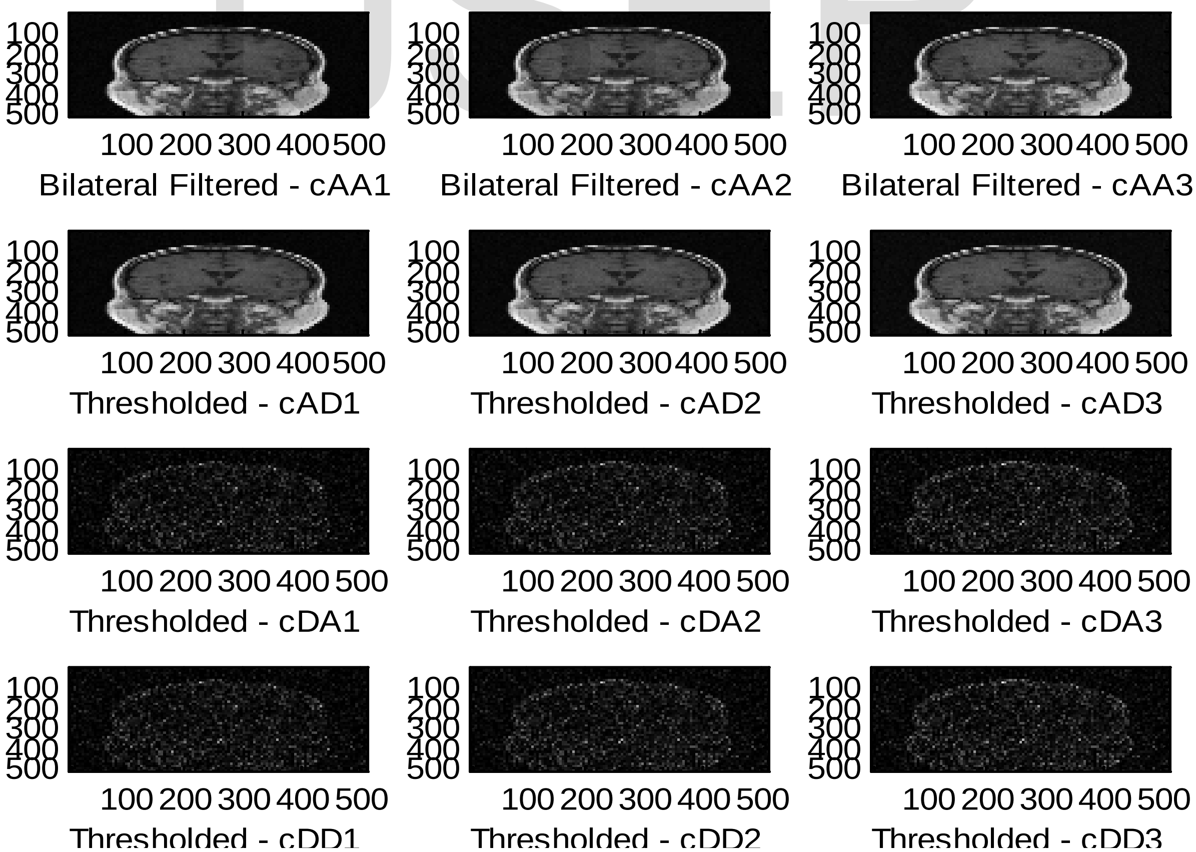

Figure 5: Wavelet Decompostion - Bilaterally filtered approximations and thresholded details after PWS

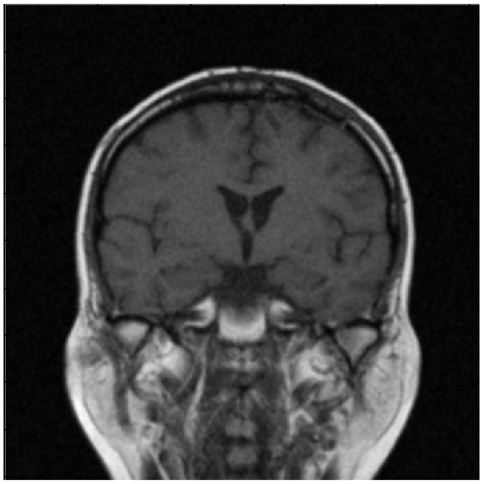

Figure 6 :Denoised Output

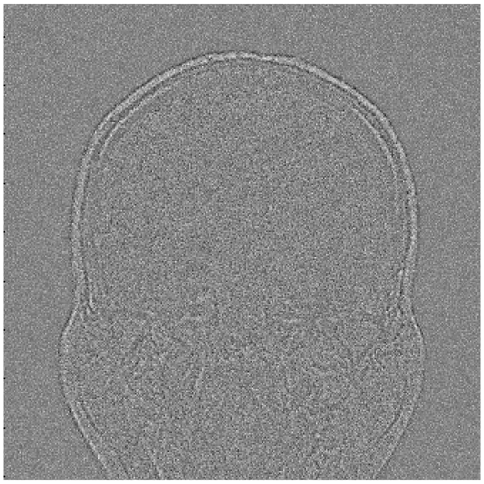

Figure 7 : Residue

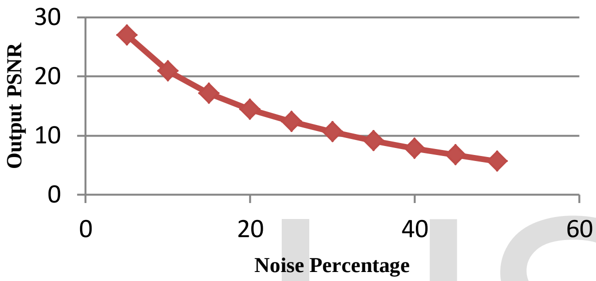

Figure 8: Plot of Output PSNR .vs. Noise Percentage

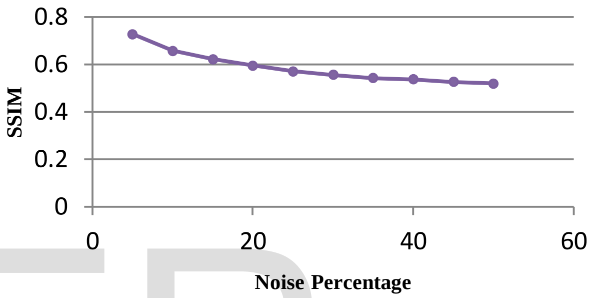

Figure 9: Plot of SSIM .vs. Noise Percentage

CONCLUSION

The proposed pixelwise estimate based on wavelet domain coefficients combined with soft thresholding and bilateral filtering provides significant improvement in the signal to noise ratio.

The PWS is computationally less complex than the conventional S estimate and is more efficient than the MAD in representation of noisy data. Further UDWT combined with thresholding and bilateral filter preserves the structural details. The quality metrics prove the efficiency of the proposed method.

REFERENCES

[1] Gudbjartsson.H and Patz.S , "The Rician distribution of Noisy MRI data", *Magnetic Resonance in Medicine*, vol. 34, no. 6, pp. 910-914.,1995.

[2] P. J. Rousseeuw and C. Croux, "Alternatives to the Median Absolute Deviation", *Journal of the American Statistical Association*, vol. 88, no. 424, pp. 1273–1283, 1993.

[3] Vladimir Crnojevi´c and Nemanja I. Petrovi´c," Impulse Noise Filtering Using Robust Pixel-Wise S-Estimate of Variance ", Hindawi Publishing Corporation, *EURASIP Journal on Advances in Signal Processing Volume 2010*, Article ID 830702, pp. 1-10, April 2010.

[4] Anand CS, Sahambi JS,"Wavelet Domain Non-Linear Filtering for MRI Denoising", *Magnetic Resonance Imaging*, 2012, p 842–861.

[5] Anand CS, Sahambi JS,"MRI Denoising using Bilateral Filter in Redundant Wavelet Domain", TENCON, *IEEE Region 10 Conf. Washington (DC)*: IEEE; 2008. pp. 1–6.

[6] Zhang M, Gunturk BK., "Multiresolution Bilateral Filtering for Image Denoising", *IEEE Trans. on Image Processing*, 2008; 17(12):2324–33.

[7] Henkelman RM, "Measurement of Signal Intensities in the Presence of Noise in MR Images", *Med Phys 1985*; 12(2):232–3.

[8] Tomasi C, Manduchi.R, "Bilateral Filtering for Gray and Color Images", *Proceedings of the 6th International Conference on Computer Vision, Washington, DC: IEEE Computer Society*; 1998. p. 839–46.

[9] Gonzalez RC., "Digital Image Processing", 2nd ed. Upper Saddle River,NJ: Pearson Education; 2004

[10] Jan Sijbers, Arnold J. den Dekker, Paul Scheunders, and Dirk Van Dyck , "Maximum-Likelihood Estimation of Rician Distribution Parameters", *IEEE Transactions On Medical Imaging*, Vol. 17, No. 3, June 1998, p 357-361.

[11] Nowak RD, "Wavelet-based Rician Noise Removal for Magnetic Resonance Imaging", *IEEE Transactions on Image Processing*, 1999;8(10):1408–19.