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Investigation on Image Denoising Techniques of Magnetic Resonance Images

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Abstract— MR images are mostly used for clinical diagnosis for their accuracy. Even though the resolution, signal-to-noise ratio and acquisition speed have been increased, the MR images are still getting polluted. Thus, denoising is needed to be done in order to improve the accuracy of both the manual and computer aided diagnostic process. There are number of noises in digital images caused based on the nature of image acquisition or transformation. Rician noise is the kind of noise occurs in MR images. Numerous denoising techniques have been proposed to denoise Rician distribution in MR images. In this paper a survey about noises in digital images, non-local means (NLM) filtering and wavelet based MRI denoising techniques have been done. Finally, a Rician denoising method is proposed using wavelet thresholding and Rician NLM and compared with the existing methods. The PSNR values show that the proposed method yields better results.

Keywords— Noises, Rician noise, MRI, Non local means, wavelet thresholding, PSNR.

I. Introduction

MRI is a test that uses a magnetic field and radio frequency pulses to take pictures of the interior structure of soft tissue organs like brain. In many cases, MRI gives information that includes information obtained from x-ray, ultrasound or computed tomography (CT) scan.

During MRI scanning, the required body portion is placed inside a special machine (scanner) that has a strong magnet produces a strong magnetic field. The hydrogen atoms in the organ go to exited state because of magnetization. When the magnetic field is turned off, the atoms come to the ground state by releasing some energy. This energy from each tissue is captured by the imaging sensor placed around the human body. Thus, the MR images are produced 3-dimensionally by keeping each voxel correspond to each tissue in the organ. Based on the intensity values of each voxel in the images, the type of tissue is identified whether it is gray matter (GM), white matter (WM) or cerebrospinal fluid (CSF) and normal or abnormal. The visual quality of the MR image is more important in the diagnostic process. Thus, the MR images corrupted by Rician noise distribution during acquisition are needed to be denoised. There are numerous methods proposed to denoise the MR images each has its own assumptions, advantages and limitations. A survey has been made on different digital image noise models and MRI denoising methods in the present work. The remaining portions of the paper are arranged as follows. Section II contains noises in digital images, section III contains noise in magnetic resonance images, section IV contains literature survey, section V contains the proposed method, section VI contains results and discussion and finally section VII the conclusion.

II. Noises in Digital Images

Noise is a random variation of image intensity and visible as grains in the image. It may arise in the image as effect of basic physics- like photon nature of light or thermal energy of heat inside the image sensors. It may produce at the time of image capturing or transmission. Noise means, the pixels in the image show different intensity values instead of true pixel values [1]. The possible types of noises that may occur in medical images are Gaussian, speckle, Poisson and Rician noise [2].

Sources of Noises

The noise can corrupt the image either during image acquisition or during image transmission. The sources of noises are

- Environmental conditions during image acquisition
- Insufficient lighting levels
- Sensor temperature
- Irregularities in scanner screen
- Interference in the transmission channel
- Atmospheric disturbances [3-5]

A. Types of Noise Models

a) Additive Noise Model

The simplest model for intensity errors is additive noise. Random variables of image dimension are added with the image signal. This is independent of the image signal. The noisy image f is the result of addition of image signal s and the noisy signal b as given in equation 1.

$$f(i,j) = s(i,j)+b(i,j) \tag{1}$$

b) Multiplicative Noise

This is signal dependent noise model. The noisy image contains the signal as multiples of unwanted random signals. The noise model is given in equation 2.

$$f(i,j) = s(i,j) * b(i,j) \tag{2}$$

c) Gaussian Noise

Gaussian noise model is an additive noise model that follows Gaussian or normal distribution. Since it is additive in nature, it doesn't depend on the intensity value of the independent pixel. All the image pixels deviate from their original values following the Gaussian curve. That is for each image pixel with intensity value f_{ij} (1<=i<=p, 1<=j<=q for an pxq image), the corresponding pixel of the noisy image g_{ij}, is given by,

$$g_{ij} = f_{ij} + n_{ij} \tag{3}$$

where n drawn from zero-mean Gaussian distribution [3]. The probability density function is,

$$p(x)=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{4}$$

μ is the mean and σ the standard deviation of the random variable x.

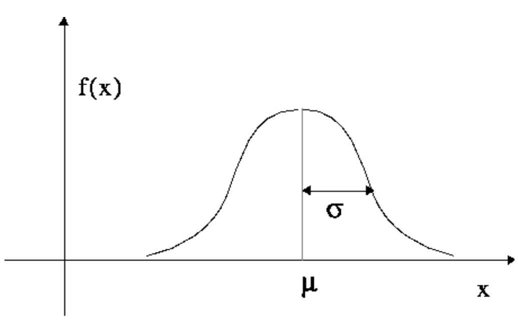

Figure 1: Gaussian curve

III. IMPULSE NOISE

Salt and Pepper noise is the impulse type of noise that contains either minimum or maximum intensity values. For example, for an 8-bit image g, the value for pepper noise is 0 and for salt noise are 255. This noise is caused due to data transmission errors. The probability density function (PDF) for this type of noise is [4],

$$P(f)=\begin{cases} P_a \text{ for } f = a \\ P_b \text{ for } f = b \\ 0 \text{ otherwise} \end{cases} \tag{5}$$

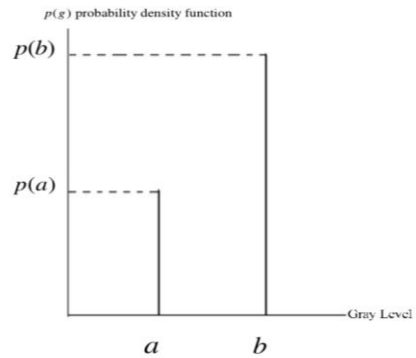

Figure 2: PDF of salt and pepper noise

IV. POISSON NOISE

It is a signal dependent, often seen in photon images. The noise variance is proportional to the original pixel intensity value. It is also called as Quantum or short noise. The noise model is described as,

$$g_{ij} \sim \frac{1}{\lambda} Poisson\{\lambda f_{ij}\} \tag{6}$$

λ is the expected number of photons per unit time interval. The poisson distribution curve is shown in Figure 3 [5].

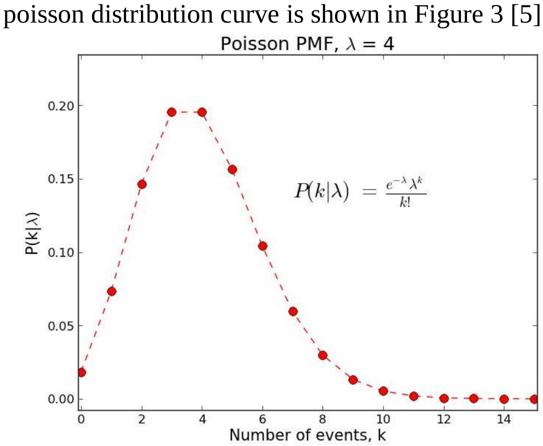

Figure 3: Poisson curve

V. RAYLEIGH NOISE

This noise present in radar range images. It follows the Rayleigh distribution as,

$$P(x)=\begin{cases} \frac{2}{b}(x-a)e^{\frac{-(x-a)^2}{b}}, & for\ x \geq a \\ 0 & , for\ x < a \end{cases} \tag{7}$$

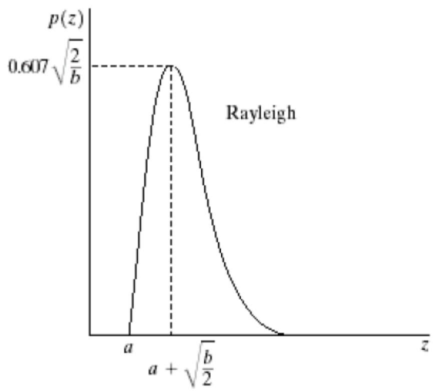

Figure 4: Rayleigh curve

VI. *EXPONENTIAL NOISE*

Its special case of Gamma noise where b=1. The probability density function is [6],

$$p(x) = \begin{cases} a e^{-ax} & for\ x \geq 0 \\ 0 & for\ x < 0 \end{cases} \quad (8)$$

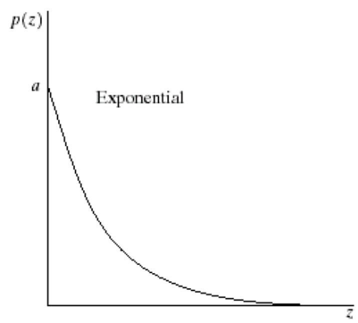

Figure 5: Exponential distribution

VII. *GAMMA NOISE*

Laser based images are prone to Gamma noise with Gamma distribution as shown in Figure 4 [7]. And the probability density function is,

$$p(x) = \begin{cases} \frac{a^b x^{b-1}}{(b-1)!} e^{-ax} & for\ x \geq 0 \\ 0 & for\ x < 0 \end{cases} \quad (9)$$

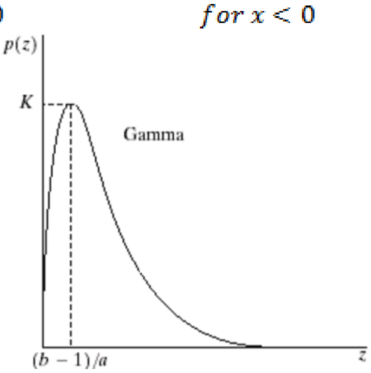

Figure 6: Gamma distribution

VIII. *UNIFORM NOISE*

The uniform noise also known as quantization noise, caused by quantizing the pixels of the image to a number of distinct levels. The level of gray values of the noise is uniformly distributed across a specified range. It is neutral or unbiased noise [8].

$$p(x) = \begin{cases} \frac{1}{b-a} & if\ a \leq x \geq b \\ 0 & otherwise \end{cases} \quad (10)$$

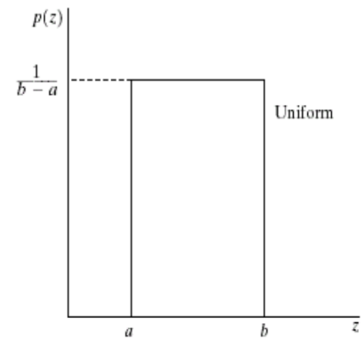

Figure 7: Uniform distribution

IX. *SPECKLE NOISE*

Speckle is a signal dependent noise with multiplicative nature. It affects inherent characteristics of coherent imaging including ultra sound, SAR and laser images. The speckle noise model has the following form,

$$g_{i,j} = \in_{i,j} + f_{i,j} * n_{i,j} \quad (11)$$

where

$g_{i,j}$ – observed noisy image

$n_{i,j}$ – multiplicative component of speckle noise

$\in_{i,j}$ – additive component of speckle noise [9,10].

X. NOISE IN MAGNETIC RESONANCE (MR) IMAGES

A) Rician Noise

MR imaging is a notable technique, provides high details about the soft tissue organs like brain in the human body [11]. It can characterize and discriminate among tissues using their physical and biochemical properties. The MR images are sectional with equivalent resolution in all the projections. The MR image is commonly reconstructed by computing inverse discrete Fourier transform of the raw data acquired from both real and imaginary channels in k-space, each of which is affected by additive white Gaussian noise [12, 13]. It is common practice to transform the complex valued images into magnitude and phase images. Thus, the probability density function (PDF) of such non-linear operation is changed. The Rician distribution or the Rician noise is locally signal dependent.

$$p_{m\,(M|A,\sigma_n)} = \frac{M}{\sigma_n^2} e^{-\frac{(M^2+A^2)}{2\sigma_n^2}} I_0\left(\frac{AM}{\sigma_n^2}\right) u(M) \quad (12)$$

$I_0(.)$ – modified zeroth order Bessel function

σ_n^2 – the noise variance

A- True signal intensity
M – Observed noisy intensity
u(.) –Heaviside step function
For higher SNR (>3) the Rician follows Gaussian distribution with mean $\sqrt{A^2 + \sigma_n^2}$ and variance σ_n^2 given as,

$$p_{m\,(M|A,\sigma_n)} \approx \frac{1}{\sqrt{2\pi\sigma_n^2}} e^{-\left(M^2 - \sqrt{A^2+\sigma_n^2}\right)/2\sigma_n^2} u(M) \tag{13}$$

At very low SNR(<0) the Rician distribution follows Rayleigh distribution.

$$p_M(M, \sigma_n) = \frac{M}{\sigma_n^2} e^{-M^2/2\sigma_n^2} u(M) \tag{14}$$

Between low and high it is neither Rayleigh nor Gaussian as shown in Figure 8 [14, 15].

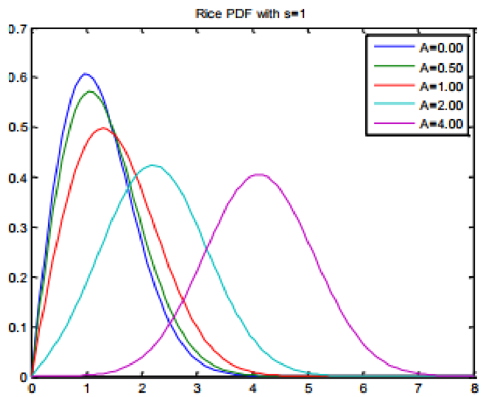

Figure 8. Rician Distribution

The visual quality of the MR image helps in obtaining the accurate results from segmentation, classification, 3-D image reconstructions and registration like automatic processes. This accuracy may get degraded by the noise present in it. Thus, removal of noise from MR images plays main role in the accuracy of diagnostic tasks. Denoising is performed in two typical ways, one is to acquire the data several times and average them, and the other way is to denoise the image with a post processing method. This post processing denoising is performed in numerous ways such as filtering techniques, domain transform approaches and statistical approaches. The literature contains few of the denoising methods based on NLM filtering and domain transform methods. The proposed method has been compared with some methods in literature.

XI. LITERATURE

Buades et al proposed the non-local means (NLM) filter for denoising digital images. This filter makes use of the similarity between the pixels in the entire image whereas the other filters make use of the similarity of the neighbourhood pixels [16]. Manjon et al. have modified the original NLM algorithm to denoise MR images where the similarity measure is the combination of various channels [17]. Manjon et al have tried to apply the Non local Means filter for random noise removal in MR magnitude images. Experiments were carried out in different noise levels in order to find optimum parameters to fit with specific characteristics of the noise in MR magnitude images [18]. NLM based filtering techniques have been applied for denoising MR images with the assumption of additive white Gaussian noise, thus fails to preserve the MR signal at low SNR values. Douli et al. has proposed an alternative formulation of NLM that considers Rician statistics of MRI noise and introduces a new similarity measure for NLM filtering of MRI [19]. Computational complexity is the main disadvantage of the NLM algorithm especially on 3D MRI data. Coupe et al. proposed an optimized parallelized implementation of NLM algorithm that decreases the computational time up to the factor of 50 [20]. This work has been further developed as optimized blockwise NLM filter for denoising 3D MR images. This is achieved by tuning of smoothing process, pre selection of neighbourhood voxels, blockwise implementation and a parallelized computation [21]. In [22], Coupe et al. has proposed a fully automatic 3D optimized blockwise NLM filter with wavelet subbands mixing for denoising MR images.

Gal et al. has proposed Dynamic NLM for denoising dynamic contrast enhanced MR images. The redundancy of information from various volumes acquired at different times has been used in neighbourhood selection [23]. Since in MR images, the regions with lower SNR follows Rayleigh noise distribution and regions with high SNR follows Gaussian noise distribution, the denoising method must consider the local noise distribution while removal of noise. Manjon et al. [24] have proposed the adaptive NLM algorithm where the denoising is limited based on the local noise level of the image. This is implemented by means of local noise estimation method. Liu et al. have implemented NLM filter on 3D MR squared magnitude images, considering the characteristics of Rician noise. Then the unbiased correction is carried out to reduce the noise disturbance [25]. Manjon et al. has proposed a 3D MR image denoising by making use of sparseness and self-similarity properties. In this method a 3D cosine transform based hard thresholding and a 3D NLM filter is applied [26]. Wiest et al. proposed a method Rician-NLM (RNLM) makes use of the self-similarity weight of the current pixel as the maximum weight among the neighbourhoods [27]. Xinyuan et al. extended [27] method named RNLM-CPP, removes the Gaussian and Rician noise by the combination of patch/pixel similarity. The limitation is, when extended to 3D data increases the computational time [28].

Jian et al. have proposed pre-smooth non-local means (PSNLM) filter by considering both Rician and NLM filter characteristics. It is a combination of pre-smoothing and image transformation. The noisy image is transformed in to an image in which the noise is treated as additive noise, and then it is pre-smoothened with a traditional denoising method followed by NLM filter and finally inverse transform is performed on the denoised MRI [29].

Jan et al. in [30] proposed a two-step denoising procedure where bias correction is performed on the squared magnitude image and then denoising is performed on square root of the image in wavelet domain. This method gives better results in denoising correlated noise than existing MRI denoising techniques. Robert proposed a wavelet based Rician noise removal method that adapts to variations in both signal and noise. This filter reduces Rician noise contamination in both high and low SNR regions [31]. In [32], Kinita et al. has applied DWT in order to threshold the noises from the selected high frequency coefficients of the noisy image. Soft thresholding, hard thresholding and Bayes thresholding has been tested to denoise the noisy image and compared with the proposed method which yields better results. Kalaiselvi et al have proposed a new thresholding technique that denoises the Rician distributed noisy MRI data with improved contrast [33]. This method is refered as Novel-WT in this paper.

A. Performance Parameters

For analysing the performance of the denoising algorithm, following parameters are calculated.

a) Mean Square Error (MSE): It is the cumulative square error between the original and the denoised image defined by:

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j)-g(i,j)\|^2 \qquad (15)$$

where, f is the original image and g is the denoised image. The dimension of the images is m x n and i, j are the indices. Thus, MSE should be as low as possible for effective performance.

b) Peak signal to Noise ratio (PSNR): PSNR is the ratio between maximum possible power of a signal and the power of distorting noise which affects the quality of its representation. It is defined by:

$$\mathrm{PSNR} = 20\, log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right) \qquad (16)$$

where MAX_f is the maximum signal value that exists in our original "known to be good" image.

c) Bits Per Pixel (BPP): It is defined as number of bits required to compress each pixel. It should be low to reduce storage requirement.

D) Signal to Noise Ratio is defined by the power ratio between a signal and the background noise.

$$SNR = \frac{P_{signal}}{P_{noise}} \qquad (17)$$

where *P* is average power. Both noise and power must be measured at the same points in a system, and within system with same bandwidth [8].

XII. METHOD

Based on the literature, a combination of wavelet based thresholding and non-local means filter has been proposed to remove Rician noise from T1-weighted MR brain images obtained from Brainweb data. The flowchart of the proposed method is shown in Figure 9.

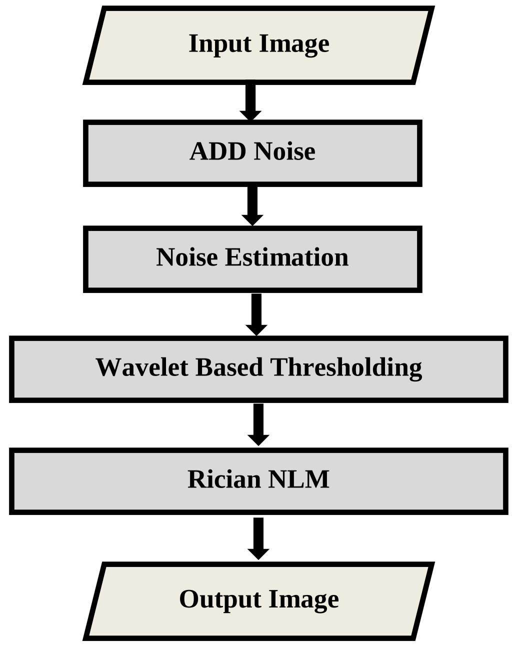

Figure 9: Flow chart of the proposed method

As in flow chart the proposed method contains the following steps. Addition of Rician noise, estimation of noise standard deviation, wavelet based thresholding followed by Rician non local means filtering technique.

B. Noise creation and estimation

The noise is introduced in the original image in different levels using the algorithm proposed by Coupe et al. in [34]. The noisy image N(i,j) is obtained using the formula,

$$N(i,j) = \sqrt{(A(i,j) + level * rand(m,n))^2 + (level * rand(m,n))^2} \qquad (18)$$

where, A(i,j) is the original image of mxn size with i,j as the pixel indices. level is the applied noise level obtained as a product of noise percentage and maximum intensity value in the original image. Noise estimation is performed using the local skew and variance as proposed by [35] is shown in the equation 19.

$$\sigma^2 = \sigma_L^2 * \varphi \qquad (19)$$

where σ^2 is the noise variance, σ_L^2 is the local estimation of variance and φ is the correction factor computed using the skewness as in [35].

C. Wavelet Based Thresholding

The noisy image is decomposed into approximation and detail coefficients in a single level decomposition using db8 wavelet. After decomposition, thresholding is done on the signal coefficients for the number of decomposition levels. The denoising method may corrupt the image while removing the noise. The noisy signal (u) is considered as the combination of the original (f) and the noise (g) signal.

$$u=f+g \tag{20}$$

The threshold value is estimated using the threshold function proposed by [33],

$$T = \frac{\sigma^2}{|Std(D_L)|^2} \tag{21}$$

where σ^2 is the estimated noise, D_L is the standard deviation of the detail coefficients at different levels(L). Using the optimal threshold T, the coefficients of the signal are denoised in hard thresholding technique. After thresholding, the decomposed wavelet coefficients are reconstructed back to obtain the denoised image with its own dimensions. This is done for the number of decomposition levels.

D. Rician NLM

The thresholded image is then filtered using the non-local means filter for Rician noise where the denoised image is obtained by,

$$NLM_f(X) = \sqrt{\left(\sum_{x_i \in V} W_i X_i^2\right) - 2\sigma^2} \tag{22}$$

where

σ^2 - variance of the noise
X_i – i^{th} pixel of the noisy image
V – search volume
W_i – similarity weight calculated using

$$W(x_i, x_j) = \frac{1}{Z_i} e^{\frac{-\|u(N_i)-u(N_j)\|^2 a}{h^2}} \tag{23}$$

where, N_i- cubic block centered at x_i with size $(2a+1)^3$.

a - the distance of the neighbourhood from the current pixel.
$u(N_i)$ is the vector consists of intensity values of N_i block.

Z_i - $\sum_{j \in N_i} e^{\frac{-\|u(N_i)-u(N_j)\|^2 a}{h^2}}$ the normalization constant ensuring that $\sum_{x_j \in u} w(x_i, x_j) = 1$ where u is the noisy image.

h is the decay control parameter usually taken as the standard deviation of noise estimated using the noise estimation method defined above.

$\|u(N_i) - u(N_j)\|^2$ is the Euclidian distance between the voxels x_i and x_j computed between the search windows (N_i) and (N_j). The maximum weight, max $(w(x_i, x_j))$ is assigned as the weight for the current i^{th} pixel i.e. $w(x_i, x_i)$.

XIII. RESULTS AND DISCUSSION

The proposed method performs wavelet based thresholding in order to reduce noise coefficients from the noisy image in prior to the NLM filtering technique. Then the non-local means filtering technique is applied. The proposed method is tested on the T1-W images obtained from Brainweb method has been analysed with the help of PSNR calculation. The PSNR results obtained from the proposed method in both 1-D and 3-D data are compared with some of the Rician denoising methods such as Novel WT [33], RNLM [26], UNLM [18], and ABONLM [24] from literature. In 1-D method, the neighbourhoods are considered with in the image plane. In 3-D method the neighbourhoods are taken from both previous and successive slices of the current slice in 3-D MR data. the PSNR values obtained from different denoising techniques for varying noise levels are listed in table 1 and the resultant denoising MR images are shown in Figure 10 for visual comparison.

Table 1: PSNR value comparison

Methods	Noise (%)		
	3	5	9
Novel WT	32.13	27.79	22.79
RNLM	32.73	29.75	27.58
UNLM	34.0421	30.67	29.27
ABONLM	32.35	28.64	24.38
Proposed-1D	33.13	29.89	28.73
Proposed-3D	34.24	30.27	29.08

From the results, the proposed 3D as well as 1D methods yield better results when compared with the other proposed methods.

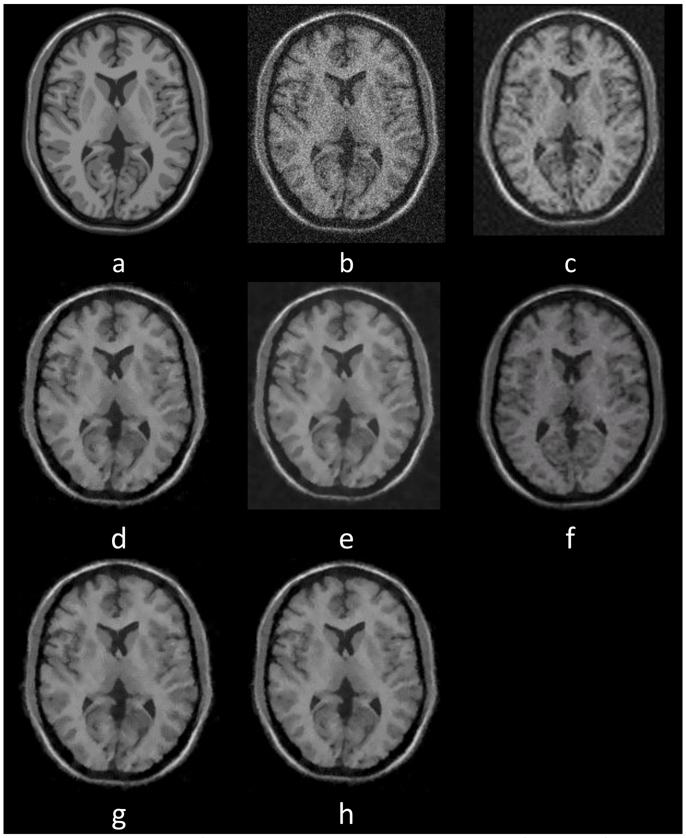

Figure 10: Results of the above said proposed methods for 9% of Rician noise. a. Original noise free image, b. Noisy image, c. Result of Novel WT, d. Result of UNLM, e. Result of RNLM, f. Result of ABONLM, g. Result of Proposed 1D, h. Result of Proposed 3D.

XIV. Conclusion

MRI is an important medical imaging technique used in accurate diagnosing than other medical imaging techniques. The noise created during acquisition degrades the accuracy. Thus, denoising is performed in order to remove noise and improve the quality of the polluted image. This paper summarized the noises in digital images, noise in MR images, MRI denoising based on NLM filter and wavelet transform techniques and proposed a Rician denoising method as a combination of wavelet transform and non-local means filtering technique. PSNR value was computed in order to analyse the performance. The results show that the proposed method yields better results than few of the methods from literature.

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