MRI denoising using UNLM filter in spatial domain

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***Abstract*—**MRI is used in the medical areas to provide a high quality imaging of the soft tissues of the human body. However, the MRI scanner technology has undergone a lot of improvements in the spatial resolution, speed of acquisition and signal to noise (SNR) ratio. But still the MRI images are corrupted by so many artifacts and noises. Identification and the reduction of these noisy components in MRI images is essential to improve the validity and accuracy of technologies designed to map the structure and function of the human body. Rician noise is commonly found noise in MRI images. The main aim is to study and improve the performance of the Unbiased Non Local Means filter to remove the rician noise from MRI images. As the UNLM filter is the extension of the NLM filter. NLM filtering takes the mean of all the pixels in the image weighted by how similar these pixels are to the target pixel, which may include pixels whose original gray value do not match the value of the original central pixel. The performance of the UNLM filter can be improved by providing only the right pixels for NL means averaging process in the squared neighborhood.

***IndexTerms*—MRI, NLM filtering, Rician noise, NL means averaging, UNLM filtering.**

I. INTRODUCTION

MRI images are affected by so many artifacts and noises. One of these artifacts and noise sources is rician noise. This type of noise seriously degrade the acquisition of quantitative measurements from the MRI data. This paper aims to improve the performance of the Unbiased Non Local Means filter to remove the rician noise from MRI images.

The NLM algorithm has been derived from the neighborhood filters. It takes the benefit of the higher degree redundancy in the natural image with the assumption that each and every small patch in the natural image has so many identical patches in the that image.

$$NLM(Y(p)) = \sum_{\forall q \in Y} w(p,q) Y(q) \quad (1)$$

$$0 \leq w(p,q) \leq 1 \ \sum_{\forall q \in Y} w(p,q) = 1 \quad (2)$$

Here, p is the point to be filtered and q is representing each and every one of the pixels in that image. The weightage $w(p,q)$ is based upon the similarity between the neighborhoods that is Np and Nq of pixels p and q. Ni has been defined as the squared neighbourhood window that is centered around the pixel i with a user-defined radius of $Rsim$. The similarity that is $w(p,q)$ will be then calculated:

$$w(p,q) = \frac{1}{Z(p)} e^{-\frac{d(p,q)}{h^2}} \quad (3)$$

$$Z(p) = \sum_{\forall q} e^{-\frac{d(p,q)}{h^2}} \quad (4)$$

Here, $Z(p)$ denotes the normalized constant, h is the exponential decay control parameter and d is denoting the Gaussian weighted Euclidian distance of all of the pixels of each and every neighbourhood:

$$d(p,q) = G\rho ||Y(Np) - Y(Nq)||^2 \quad (5)$$

Here, $G\rho$ denotes normalizing Gaussian weighting function with the zero mean and ρ standard deviation (that is usually set to 1) that will penalize the pixels far from the center of the neighbourhood window by assigning the more weight to the pixels near the center.The centered pixel of the Gaussian weighting window is set to the same value that the pixels at a distance 1 in order to avoid the over-weighting effects.

In equation (1) there will be special case when $p == q$ .As the self similarty will be high, it will generate an over - weighting effect. In order to solve this problem $w(p,q)$ will be calculated as:

$$w(p,q) = \max(w(p,q) \forall q \neq p) \tag{6}$$

The magnitude of the MRI signal is always the square root of the sum of the squares of the Gaussian distributed real and imaginary parts.That is , it follows the Rician distribution.In the lower intensity regions of MRI image, the Rician distribution approaches to the Rayleigh distribution but in the higher intensity regions it tends to be a Gaussian distribution.As the result of this the image contrast will get reduced.This type of problem can be solved by the filtering of the square of the magnitude of the image. In this squared magnitude image, the noise bias is no longer signal dependent and this can be efficiently removed. The bias will be equal to $2\,\sigma^2$.

$$UNLM(Y) = \sqrt{NLM(Y)^2 - 2\sigma^2} \tag{7}$$

Where $\sigma = \sqrt{\mu}/2$ and μ is the mean of the background of the squared magnitude image which is selected using the thresholding method.

II. PROPOSED TECHNIQUE

The performance of the UNLM can be further enhanced by using the adaptive method. The search region in NLM is usually a rectangular neighborhood, centered at the POI, which may include pixels whose original gray value do not match the value of the original central pixel.

Consequently, their participation in the weighted averaging process degrades denoising performance. This method provides only the right pixels for NL means averaging process in the squared neighbourhood.Before discussing the proposed technique, firstly we will explain the various concepts that are used in addition to UNLM filter in this proposed technique:

Gaussian Filter: The gaussian filter is a type of non linear filters. This filter does work on the idea of moving window. The window is of size $3 \times 3, 5 \times 5\ or\ 7 \times 7$. Gaussian filter may be obtained from the Gaussian function of two variables as:

$$h(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{8}$$

Here, σ is the satandard deviation and x and y are the coordinates that are assumed to be integers. The amount of smoothing caused by the gaussian filter depends on the size of window and the value of σ.It will reduce gaussian noise but blurs the fine details present in the image.

Thresholding: Thresholding is the process by which an image is classified into two parts that is a lower level intensity region and a higher level intensity region.Due to its significant properties, computational speed and simplicity, it plays a significant role in segmentation.The basic idea behind the thresholding is that if an image comprises of dark background and the objects that belongs to it are represented by white then in order to separate the objects from the background a binary image can be created from the original image as follows:

$$t(x,y) = \begin{cases} 1 & if\ f(x,y) > T \\ 0 & if\ f(x,y) < T \end{cases} \tag{9}$$

Here, T is a threshold known as the **global thresholding**. If the value of T changes over the image, it is known as the **variable threholding**. A **multiple thresholding** can be represented as:

$$\mathrm{t(x,y)} = \begin{cases} \mathrm{a} & \mathrm{if}\ \ \mathrm{f(x,y)} > T2 \\ \mathrm{b} & \mathrm{if}\ \ \mathrm{T1} < f\mathrm{(x,y)} \leq \mathrm{T2} \\ \mathrm{c} & \mathrm{if}\ \ \mathrm{f(x,y)} \leq \mathrm{T1} \end{cases} \tag{10}$$

As the proposed technique consists of three steps:

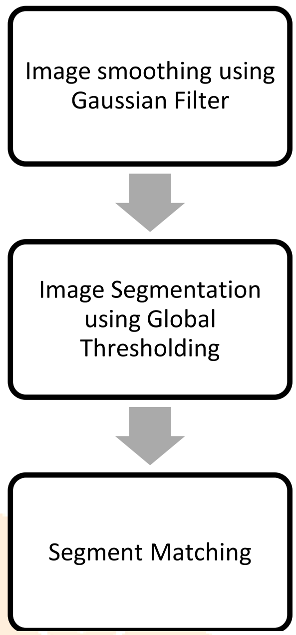


Figure 1. Proposed Technique

(1) **Image Smoothing using Gaussian Filter:** The MRI image $f(x, y)$ is smoothed in this step using Gaussian filter as in eq. (8) that results in an imge $g(x, y)$.By smoothing,the image becomes less noisy.This process improves the segmentation of the image.

(2) **Image Segmentation using Global Thresholding:** In this step, the image $g(x, y)$ is classified into two parts that is a lower level intensity region and a higher level intensity region using eq. (9) resulting in a segmented image $g1(x, y)$.

(3) **Segment Matching:** As in $eq.$ (1) of NLM filter,where p is the pixel to be filtered, q is representing all pixels in that image and $w(p, q)$ in eq. (3) is representing the weight based on the similarity between p and q in the image $f(x, y)$. Before calculating the weight $w(p, q)$ using the eq. (3) , the pixels corresponding to p and q in the segment $g1(x, y)$ are matched.

- If the intensity values at pixels p and q are same(i.e. both are 0's or 1's) in the segment $g1(x, y)$, then the $w(p, q)$ is calculated using eq. (3) of the NLM filter.
- If the intensity values of these aren't same then the pixel q will not be considered in the averaging process of the pixel p.

III. EXPERIMENTAL RESULTS

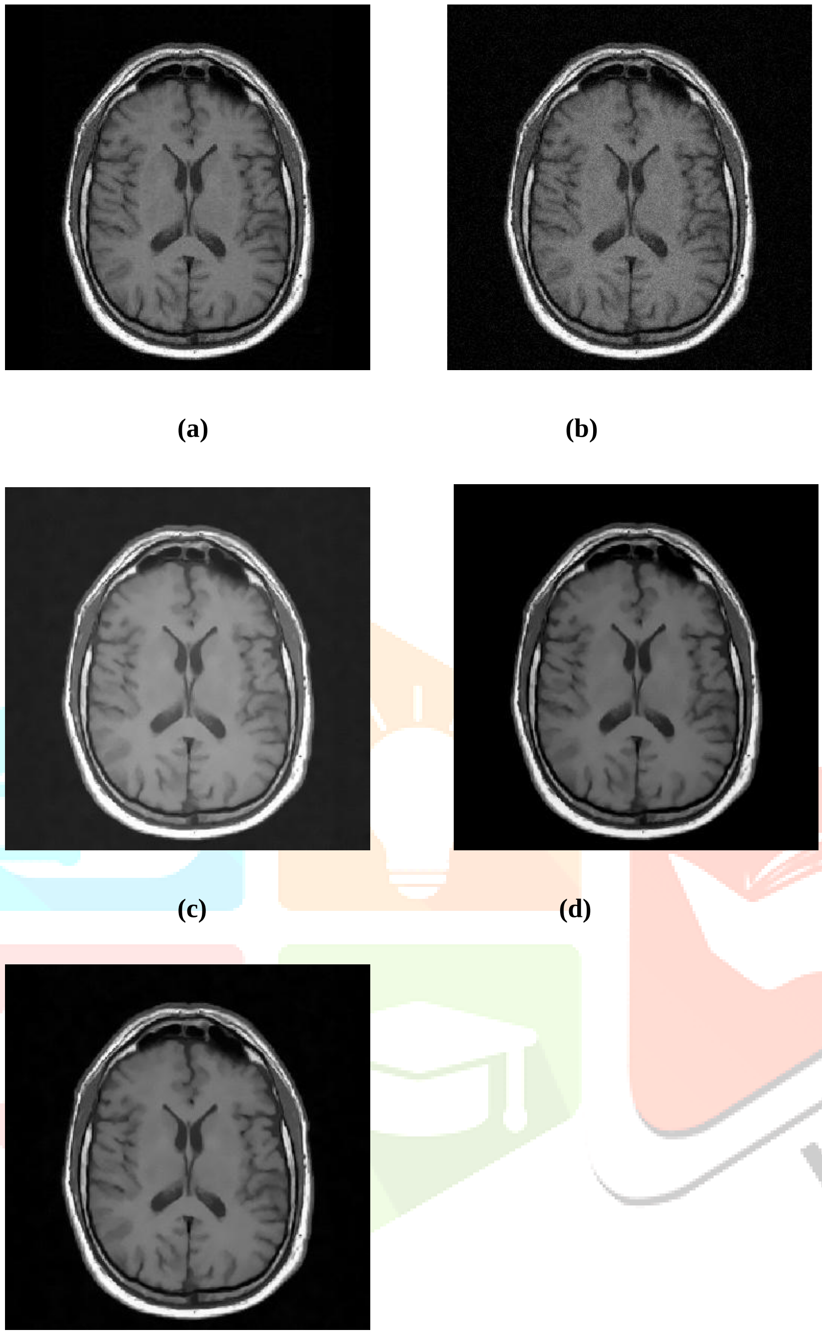
In order to compare the performance of the proposed technique with NLM and UNLM filters experiments have been conducted on the three MRI images. All of the experiments have been conducted on MATLAB 7.10.0 (R2010a). The parameters values that have been used in the NLM, UNLM and Proposed technique are:

$Rsearch = 5$, that is the radius of the search window

$Rsim = 2$, that is the radius of the neighbourhood window and

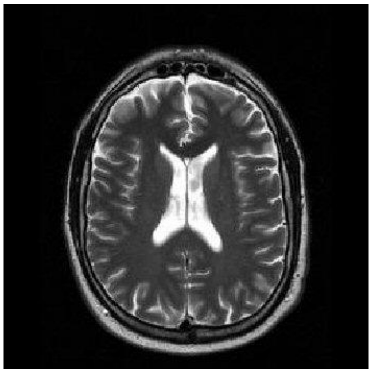
$h = 1.2\sigma$, that is the exponential decay control parameter.

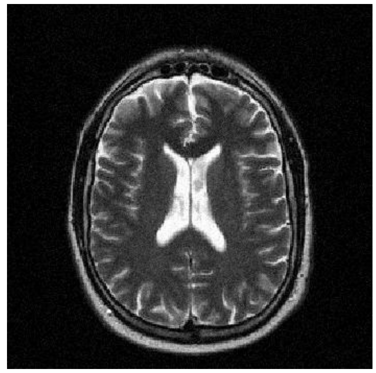
The following figures represents the original MRI images, corresponding rician noised images, NLM filtered, UNLM filtered and proposed technique filtered images respectively. Further, The comparative performance of NLM filter, UNLM filter and proposed technique is given in the table 1 and table 2 in terms of filter assessment metric namely PSNR and MSSIM respectively.



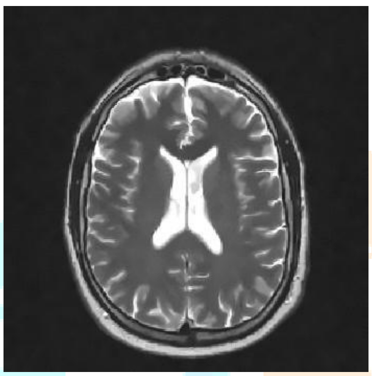
(e)

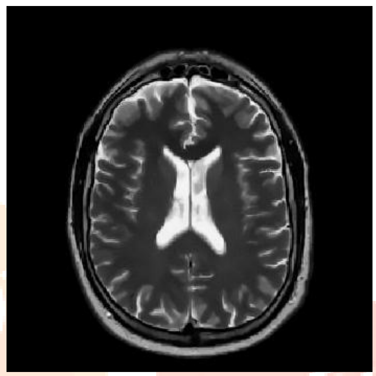
Figure 2. (a) brain_mri_t1 noise free image (b) noisy image (c) NLM filtered image (d) UNLM filtered image (e) Proposed technique filtered image.



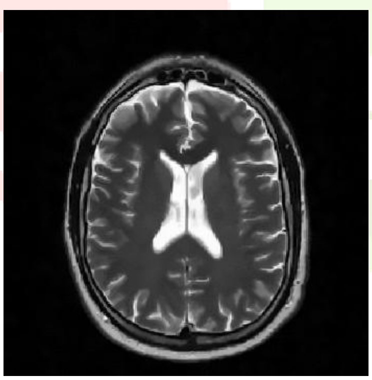


(a) **(b)**



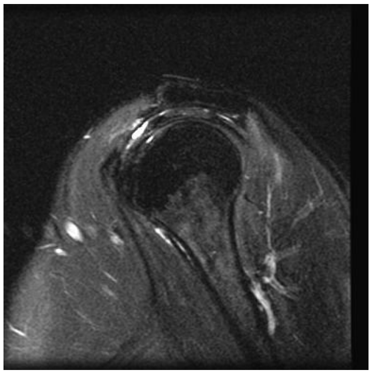


(c) **(d)**

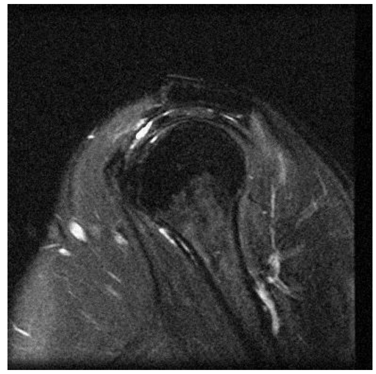


(e)

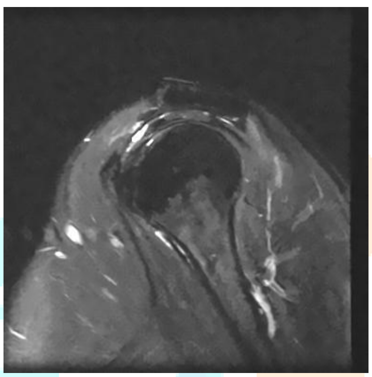
Figure 3. (a) brain_mri_t2 noise free image (b) noisy image (c) NLM filtered image (d) UNLM filtered image (e) Proposed technique filtered image.



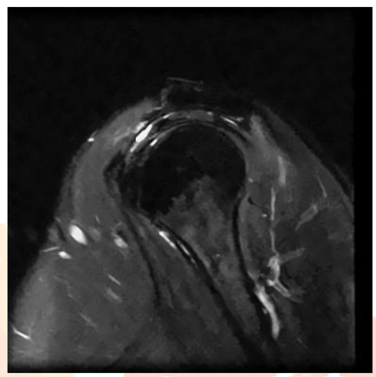
(a)



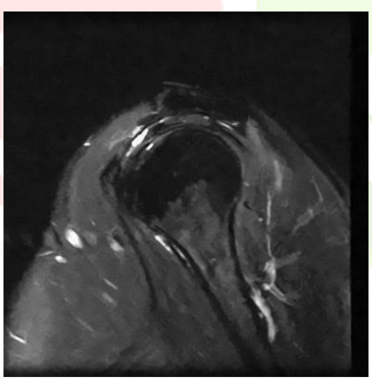
(b)



(c)



(d)



(e)

Figure 4. (a) shoulder_mri_t2 noise free image (b) noisy image (c) NLM filtered image (d) UNLM filtered image (e) Proposed technique filtered image.

Table 1. Average PSNR of the denoised images

Image → Filter↓	**brain_mri_t1 image**	**brain_mri_t2 image**	**shoulder_mri_t2 image**	**Average PSNR**
NLM filter	32.5214	32.4659	33.2834	32.7569
UNLM filter	34.0807	33.1355	34.2635	33.8265
Proposed Technique	34.4957	34.2373	34.9427	34.5585

Table 2. Average MSSIM of the denoised images

Image → Filter↓	**brain_mri_t1 image**	**brain_mri_t2 image**	**shoulder_mri_t2 image**	**Average MSSIM**
NLM filter	0.9054	0.9052	0.8984	0.903
UNLM filter	0.9102	0.9108	0.9004	0.90713
Proposed Technique	0.9204	0.9260	0.9115	0.9193

IV. CONCLUSION

The comparative analysis represents that the proposed technique provides better performance in terms of quantitative results of PSNR and MSSIM as compared to the perfomance of NLM and UNLM filters. Therefore, the Proposed technique performs better MRI denoising.

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