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Research Article

Analysis of MRI Enhancement Techniques for Contrast Improvement and Denoising

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Abstract

MRI images often suffer from low contrast and noise, especially in cardiac and brain imaging. Only a skilled radiologist can make an effective diagnosis and this limits its use in a wide medical network. This noise hampers further tasks such as segmentation of the important features and classification of images, 3-D image reconstruction and registration. The noise in MR images will change the value of amplitude and phase of each pixel. As a result, the visual quality gets deteriorated and perfect diagnosis of the disease becomes difficult. Enhanced processing of medical images is therefore necessary for obtaining high quality images of human tissues and organs. The SNR of the images used during quantitative analysis can be improved by using denoising methods, which improves the image quality by reducing the noise component thereby preserving all the image features. Although medical images are corrupted by different types of noises, this paper focuses on noise prominently in MR images which are Gaussian and Rician distributed. This work aims to improve the contrast and the SNR of MR images by taking into account both the homogeneous and non homogeneous nature of noise. The proposed approach provides better contrast using histogram equalization and effective denoising is achieved using Non Local Means (NLM) filter. The results are validated on simulated and real data using both visual quality assessments and performance metrics.

Keywords: *Anisotropic Diffusion, Denoising, Histogram Equalization, MRI, Non Local Means filter.*

1. Introduction

Medical image enhancement enables identification of the desired region in the image by enhancing the required areas. The problem of medical image enhancement became more important in the last decade, as it occupies a very important position in various disease diagnoses especially in non-invasive treatment and clinical study. Imaging helps the radiologists to visualize and examine the images for understanding the abnormalities in internal structures. In medical imaging, it is very important to obtain precise images to facilitate accurate observations for the given application. MRI has gained wide popularity than other imaging technologies like computed tomography (CT), Ultrasound and X-ray, as it does not produce ionizing radiation and is therefore safe even under prolonged imaging durations. As MRI can easily differentiate between normal and abnormal tissue, it may be employed instead of CT in situations where organs or soft tissue are being studied. MRI acquisition helps the biomedical engineers to fully analyze the different aspects of the brain, thereby reducing the need for surgery. In medical image processing, MR images are corrupted by different type of noises which are Gaussian and Rician in nature. There are different sources for these noises among which the main sources are physiological reasons such as patient motion or blood flow or may be due to hardware reasons such as RF pulse truncation or RF interface (Maclaren, 2008). RF truncation or Gibbs ringing artefact occur in region of boundary between high and low signal intensity and is caused by the approximation errors in Fourier transform analysis. RF interface or zipper artefact occurs when the door of scanning room is open during acquisition. It is caused by external RF noise entering the room from outside electronic equipment like mobile devices or aircraft, which are picked up by the receiver chain of imaging sub-systems. It may occur in either frequency or phase direction (Blink, 2004). Many approaches have been proposed to address the difficult problem of MR image denoising. Though there are numerous advantages of MRI technology, but it generates low contrast images. One of the reasons for low contrast is presence of bulk amount of liquid in human body. It is often useful for comparing different pulse sequences to evaluate the difference between standard tissues such as gray matter, white matter, and Cerebro Spinal Fluid. Also, since noise directly impacts the accuracy of automatic approaches such as segmentation, it is important to improve the Signal-to-Noise Ratio (SNR) of images used during quantitative image analysis. The main motivation behind this paper was performing a robust method for contrast improvement and denoising of MRI in an effective way, so as to provide a good quality image which can aid in better tumor detection.

1.1 Relevance

Brain tumor is one of the major causes for the increase in

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mortality among people. A tumor is an abnormal growth of cells reproducing themselves in an uncontrolled manner. According to the news given by The Tribune India on August 22, 2013, "As many as 10 lakh cancer cases have already been detected in India in the current year, with the caseload set to shoot to 11.48 lakh by 2015 and 13.20 lakh by 2020". Brain disorders account for over 25% of total world's disease. 7137 of 122429 study deaths were due to cancer, corresponding to 556400 national cancer deaths in India in 2010 (Pubmed health, Available online at http://www.ncbi.nlm.nih.gov/pubmedhealth).The detection of brain tumor requires high resolution MRI as it is the most reliable method for assessing the tumor size and extent, as well as to discover the abnormalities at an early stage. The MR image shows the clear distinction between the tissues, bones and fluid and makes it easy to identify the tumor part of the image. But a crucial issue in image analysis is the problem of noise removal while keeping the integrity of relevant information. Enhanced processing of MR images is good for presenting clear human tissues and organs.

1.2 Outline of the paper

The rest of the paper is organized as follows. The section 2 presents the image contrast and the noise characteristics of MRI and the various denoising and contrast enhancement techniques.The section 3 explains the design methodology. The section 4 presents the performance validation and simulation results. Finally, the conclusions and future work are provided in the last section.

2. Theoretical Background

Different approaches have been used for enhancement in both spatial and frequency domain. Noise reduction becomes especially critical for the images with low SNR. Although various methods have been used for MRI enhancement, many of them could not address the problem of contrast and noise altogether; moreover they could not adapt to the noise characteristics of MRI. This section describes the contrast and noise in MRI and also discusses the popular post acquisition based denoising methods, as it is inexpensive and do not increase the overall acquisition time.

2.1 Image Contrast in MRI

The principle of MRI is based on the absorption and emission of energy in the radio frequency range of the electromagnetic spectrum.MRI relies on the relaxation properties of magnetically excited hydrogen nuclei of water molecules in the body and is ruled by the Larmor equation. The external RF pulse applied at the centre frequency causes the excitation of protons and the rotation of net magnetization. After the RF excitation pulse stops, the protons come to their lower energy state by releasing the absorbed energy known as relaxation. The three main parameters affecting contrast are Proton Density (PD), spin-lattice relaxation time (T1) and spin-spin relaxation time (T2) (Blink, 2004).The recovery of longitudinal magnetization by main magnetic field, according to equilibrium is called longitudinal relaxation or spin-lattice relaxation, as the energy is released to the surrounding tissue (lattice).The decay of transverse magnetization by external magnetic field is called transverse relaxation or spin-spin relaxation as it describes interactions between protons in their immediate surroundings (molecules). The image contrast is highly dependent on the relaxation processes, i.e., it depends on the Repetition time (TR) and the Echo time (TE).In certain instances, the intrinsic differences in T1, T2 and PD may not be sufficient to achieve the desired degree of contrast. In those cases, additional differences can be introduced by adding contrast agents like Gadolinium diethylene triamine pentaacetic acid (Gd-DTPA) which are paramagnetic chemicals and may harm the patient. Thus to a cope up with this situation, a better technique is desirable to produce high quality contrast images at a higher speed and resolution.

2.2 Noise Characteristics in MRI

The raw data obtained during MRI scanning process are complex values that represent the magnetization distribution of a volume of tissue. The real and the imaginary images are reconstructed from the acquired data by the complex Fourier transform and magnitude MRI images are normally generated by the inverse Fourier transformation from received frequency signals of an MR scanner system. The major source of the noise is random thermal noise from the patient while some additional noise arises from the acquisition hardware. The random thermal noise comes up primarily from stray currents in the body that induce random signals in the receiver coil. This thermal noise is spread throughout the raw acquired data, and when the image is reconstructed, this noise is spread throughout the voxels of the image. The result is that this thermal noise can be described as uniform random Gaussian noise, with the noise in each voxel having the same standard deviation and being independent of the noise in the other voxels. So, the noise in the k-space MR data from each coil is assumed to be a zero mean uncorrelated Gaussian process with equal variance in both real and imaginary parts. Gaussian noise is evenly distributed over the acquired MR signal and follows the Gaussian curve. This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. As Fourier transform is a linear and orthogonal transform, it preserves the Gaussian characteristics of the noise. The complex MR data is given as, $M = a + ib$. The noise added to the complex raw data is zero mean Gaussian noise $N(0, \sigma^2)$,

$$M = (a + n_{re}) + i(b + n_{im}) \tag{1}$$

The Gaussian distribution with mean $\sqrt{(A^2+\sigma^2)}$ and variance σ^2 is given as,

$$P_M(M) \approx \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-\left(M-\sqrt{A^2+\sigma^2}\right)^2}{2\sigma^2}} \tag{2}$$

Magnitude images are widely used in MRI as they obviate the problem of phase artifacts by discarding the phase information. They are formed by calculating the magnitude, pixel by pixel from the real and the imaginary images. This is a nonlinear mapping and the probability density function of the data under concern changes. So the noise no longer obeys Gaussian distribution and follows Rician distribution (Hakon *et al*, 1995). Hence the magnitude data in spatial domain is modelled as Rician distributed and the so-called Rician noise is locally signal dependent. If $|M|$ is the magnitude MRI image of a complex valued signal, then

$$|M| = \sqrt{(a + n_{re})^2 + i(b + n_{im})^2} \quad (3)$$

Thus the Rician distribution is given as,

$$P_M(M) = \frac{M}{\sigma^2} e^{\frac{-(M^2+A^2)}{2\sigma^2}} I_0\left(\frac{A.M}{\sigma^2}\right) \quad (4)$$

Here A is the pixel intensity in the absence of noise and M is the measured pixel intensity. I_0 is the modified zeroth order Bessel function of the first kind. Unlike additive Gaussian noise, Rician noise is signal dependent and consequently separating signal from noise very difficult. Rician noise is problematic especially in low SNR regimes where it not only causes random fluctuations, but also introduces a signal dependent bias to the data and reduces image contrast (Nowak *et al*, 1999). Rician noise degrades images in both qualitative and quantitative senses and hinders image analysis, interpretation and feature detection. It reduces detectability in low SNR images. Now when $A=0$, i.e., only noise is present (no NMR signal), it follows Rayleigh distribution.

$$P_M(M) = \frac{M}{\sigma^2} e^{-M^2/2\sigma^2} \quad (5)$$

At low SNR (SNR<2), noise distribution could approximate as Rician. This type of noise is signal dependent and relatively hard to be removed with conventional noise filter as it cannot adapt to the nature and location of the noise. On the other, for high signal intensities (SNR>2), the Rician data can be approximated as Gaussian. Thus, Rician noise behaves to be Gaussian distributed when the SNR is high($A \to \infty$) and Rayleigh distributed for low SNR($A \to 0$). Now for the same noise level, the Rician noise is stronger than the Gaussian noise. Consequently, it is highly desirable to develop filtering methods that can remove this noise. Thus, denoising of images has become the predominant step in medical image processing.

2.3 Related Works

Though there are many types of image denoising and enhancement algorithms, many of them could not be applied to medical images directly. A major reason is the contradiction between image denoising and enhancement. Removing noise followed by enhancement often make the edges not visible. If the noise is not completely removed, there may be chances of getting the noise also amplified. So enhancement followed by the denoising effect is done for medical images.

Contrast enhancement is a method to expand the features of interest so that they occupy a larger portion of the displayed gray level range without distortion to other features and the overall image quality. Histogram equalization (HE) is a technique by which the dynamic range of the histogram of an image is increased. It distributes pixel values uniformly such that enhanced image has a linear cumulative histogram. Histogram equalization assigns the intensity values of pixels in the input image such that the output image contains a uniform distribution of intensities (Garg *et al*, 2011). It improves contrast by obtaining a uniform histogram. A survey of contrast enhancement techniques based on Histogram Equalization is carried out by (Kaur *et al*, 2011). The major difference among the methods in Histogram Equalization is the criteria used to divide the input histogram.

Perona-Malik Anisotropic Diffusion filter (ADF) is a nonlinear smoothing filter which uses a variable conductance term, that regulates how much diffusion takes place at different locations in the data (Gerig *et al*, 1992). The anisotropic diffusion performs a piecewise smoothing of the original signal. As a result, the propagation of information between discontinuities results in regions of constant intensity or linear variations of low frequency. Here image noise is assumed to be zero mean and Gaussian distributed. It overcomes the major drawbacks of conventional filter methods, namely the blurring of object boundaries and the suppression of fine structural details. The advantage of this filtering method is that it can smooth small discontinuities caused by background noise using gradient information and can preserve large intensity variations caused by edges. But the method is iterative and cannot account for Rician noise characteristics of MRI. Later Krissian *et al*,(2009) proposed an approach that can remove Rician noise from MRI using noise driven anisotropic diffusion filter. This filter does not require the user to choose a contrast parameter for the edges of the structures like the standard Perona-Malik's filter. It relies on the local statistics of the image, i.e., local mean and local variance, and on an estimated standard deviation of the noise for the underlying noise model.

Total Variation (TV) introduced by Rudin *et al*, (1992) is based on the assumption that the image only contains white Gaussian noise. The method is iterative and TV based schemes removes noise and artefacts, while preserving edges and fine structures. In practice, the method tends to remove texture and small image structures. Tuning the parameter λ is time consuming and requires prior knowledge about noise type and variance. This filter is not optimal for MRI images with spatially varying noise levels. Another approach was described in (Guo and Huang, 2009). This adaptive TV model can handle spatially inhomogeneous noise and artefacts. Non local means (NLM)filter was proposed by (Buades *et al*, 2005) has emerged as a very simple and an effective way to reduce noise while minimally affecting the original structures of the image. The NL-means filter uses the redundancy of information in the image under study to remove the noise.

The normal methods of signal correction usually assume a uniform or spatially independent Gaussian distribution of noise standard deviation across the image. Although this assumption is true for images with high

SNR, this is no longer valid for clinical data in applications like SENSE (Sensitivity Encoding),GRAPPA(Generalized Autocalibrating Partially Parallel Acquisitions) and Diffusion Tensor Imaging(DTI) where the bias introduced by Rician noise is a serious concern. The homogeneous distribution of noise facilitates the denoising process with fewer complications. But real images are not usually corrupted with a uniform noise distribution, rather most of the images incorporate noise in the form of bursts with different intensities creating the inhomogenity. The non-homogeneity of the variance of noise arises due to the reconstruction process. Magnitude MR images follow Rician distribution. As a result, the weighted average will be biased due the asymmetry of the Rician distribution. Thus, when the SNR is small, the squared magnitude image has a noise bias which is signal independent and can be easily removed. Such a bias is equal to $2\sigma^2$ (Nowak *et al*, 1999) and therefore, a simple bias subtraction will recover its original value. Therefore Equ.(4) becomes,

$$P_M(M) = \frac{1}{2\sigma^2} e^{\frac{-(A^2+2\sigma^2+A^2)}{2\sigma^2}} I_0\left(\frac{A\sqrt{A^2+2\sigma^2}}{\sigma^2}\right) \qquad (6)$$

3. Methodology

The proposed enhancement approach can be viewed as a three stage process. Preprocessing is the basic step in any noise reduction image processing. The first stage deals with preprocessing by median filter as it produces better preprocessing with less blurring of edges. The advantage of median filtering is that, it is not affected by individual noise spikes, eliminates impulsive noise quite well, and it does not blur edges much and can be applied iteratively.

Fig.1 Proposed approach

The second stage is the contrast enhancement which increases the visibility of fine details and helps to clearly distinguish between the gray matter, white matter and CSF. This is carried out by histogram equalization because of its efficiency and simplicity. The last stage handles the denoising by non iterative Non Local Means filter as it preserves fine structures and reduces correlated noises. This hybrid approach increases the image contrast and also adapts to the homogeneous and non-homogeneous Gaussian and Rician noise characteristics. Moreover, the method also removes the bias effect introduced by uncorrelated Rician noise.

The median filtering is carried by the moving window principle where the kernel is scanned over the entire image and the centre pixel value of each window is replaced by the computed median. Now the histogram equalization stretches the resultant histogram to a new dynamic range and increases the overall contrast. Non Local Means filter is based on the assumption that the image contains an extensive amount of self similarity, every small window (patch) in a natural image has many similar windows in the same image. Non local means compares entire patches to find the pixel weights for filtering the noisy images. It works by computing the non local weights based on distances in a features space comprising the local mean value and gradients of the image (Buades *et al*, 2005). The method increases the SNR by reducing variations among pixels in the image with close similarity indices with improved accuracy. Each pixel i of the non-local means denoised image is computed as,

$$NLM[I_n](i) = \sum_{j \in I_n} w(i,j) I_n(j) \qquad (7)$$

where $I_n(i)$ is pixel being filtered, $I_n(j)$ represents each one of the pixels in the noisy image and weights satisfies the condition $0 \leq w(i,j) \leq 1$ and $\sum_j w(i,j) = 1$. Here, the weight depends on similarity between the neighbourhood window $N(i)$ and $N(j)$ of both the pixels respectively. This similarity is measured as a decreasing function of the weighted Euclidean distance. Now the weight is defined as,

$$w(i,j) = \frac{1}{Z_i} e^{\frac{-\left\|I_n(N_i)-I_n(N_j)\right\|^2}{h^2}} \qquad (8)$$

where Z_i is the normalisation constant and ensures that $\sum_j w(i,j) = 1$.

$$Z_i = \sum_{j \in I_n} e^{\frac{-\left\|I_n(N_i)-I_n(N_j)\right\|^2}{h^2}} \qquad (9)$$

h is the smoothing parameter which controls the decay of exponential function. It is given by $h = (k\ \sigma)^2$ where k is the degree of filtering and σ is the noise standard deviation. Now the Rician noise suffers from the bias effect. So a simple bias correction is added to the NLM filter to handle Rician noise. The unbiased NLM is obtained by subtracting the noise bias from the squared value of NLM. It is given by,

$$UNLM[I_n] = \sqrt{\max(NLM[I_n]^2 - 2\sigma^2, 0)} \qquad (10)$$

To avoid negative values due to the subtraction operation, the restored value of the sum of weights is calculated as the maximum of the value after bias subtraction and 0. Finally, the performance of the approach is validated using different metrics like RMSE, PSNR and SSIM.

MRIs can take great advantage of the NLM filter, since the images always suffer from Rician noise. It works by averaging pixels in nonlocal vicinities, weighting them depending on their similarity with the pixel of interest. Three parameters are need to be set to use the NLM filter- the size of the search window, the size of the neighbourhood or path window and the degree of the filtering. Among these, the size of the search and similarity or patch windows strongly influences the performance of the algorithm (Manjn *et al*, 2008). The block-wise NLM filter implementation in (Coupe *et al*, 2008) takes overlapping sets of pixels. The advantage of NLM is that the operations are performed without any iterative schemes. NLM filter provides better performance than the previous algorithms such as total variation, wavelet thresholding and anisotropic diffusion filtering.

Since the NL means filter compares not only the gray level in a single point, but also the geometrical configuration in a whole neighborhood, it allows a more robust comparison than other neighborhood filters.

4. Results and Discussions

4.1 Datasets

Experiments have been conducted on both synthetic and real MR datasets to compare the method with other denoising methods. The simulated datasets of brain MRI are obtained from the Brain-web database at the McConnell Brain Imaging center of the Montreal Neurological Institute, McGill University http://www. bic.mni.mcgill.ca/brainweb. The data set consists of T1weighted Axial, T2weighted Axial and PD images of 181 x 217 x 181 voxels. In order to validate the results, the ground truth image from the brainweb database are corrupted with different level of Rician and Gaussian noise from 3% to 12%. Rician noise was generated by adding Gaussian noise to real and imaginary parts and then computing the magnitude of the image. In the clinical data sets, the images acquired using Philips Medical Systems 1.5T Scanner were obtained from http://www.osirix viewer.com/datasets. Here, the images are acquired using spin echo (SE) sequences with long repetition time (TR) and short echo time (TE).The results are validated on T1 weighted Axial MR images of normal brain with TR = 449 ms, TE = 10 ms, 5 mm thickness and 512 x 512 resolution.

4.2 Validation Strategies

There are two criteria that are used widely to measure image quality- the visibility of artefacts and the preservation of edge details. It is usually measured by visual inspection. The difference between the original image and its denoised image shows the noise removed by the algorithm, which is called as method noise or residual image. image. It should be as similar to a white noise as possible and is required to verify the traces of anatomical information removed during denoising (Buades *et al*, 2005). The less image structures seen in it, the better the denoising performance. Here the performance of the approach is measured using different measures:
(1) Mean Square Error (MSE)
(2) Root Mean Square Error (RMSE)
(3) Peak Signal to Noise Ratio (PSNR)
(4) Structural similarity index (SSIM)

The MSE quantifies the strength of error signal and is calculated according to the formula,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - I_d(i,j)]^2 \qquad (11)$$

where *mn* is the image dimension, *I(i,j)* and $I_d(i, j)$ represents the intensities of pixels *(i, j)* in the original image and denoised image, respectively. RMSE describes how well noise is removed and is given as the square root of MSE. The MSE and the RMSE values must be small as much as possible for better denoising. The Peak Signal to Noise Ratio (PSNR) in dB is given by the formula,

$$PSNR = 10log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (12)$$

where MAX is the maximum possible pixel value of the image. Higher the PSNR, the better the denoising algorithm is. The Structural Similarity (SSIM) index (Zhou Wang *et al*, 2004) is a method for measuring the similarity between the original and the denoised images. It is based on the idea that the human visual system is highly adapted to the structural information from visual scenes. Apart from the structural changes, image quality is also affected by luminance and contrast, which must be also accounted for better quality analysis.The SSIM works as follows: let x and y be two non negative images, where as one has perfect quality. It can be defined as

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (13)$$

where C_1 and C_2 are the regularisation constants to avoid instability when $\sigma_x^2 + \sigma_y^2\ is\ \approx 0$.Its values are given as $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$ where K_1,K_2 <<1 is a small constant/regularisation parameter and L is the dynamic range of the pixel values. μ_x and μ_y are the estimated mean intensity and σ_x and σ_y are the standard deviations, respectively. The SSIM index shows how well the structures are preserved in the resultant image. It quantifies the subjective image quality better than MSE or PSNR.SSIM can be viewed as a quality measure of one of the images being compared, provided the other image is regarded as of perfect quality. As opposed to the RMSE, this index accounts for the similarity between image structures and not between grey levels. It is in the range of 0 for worst quality and 1 for images identical to ground-truth.

4.3 Simulation Results and Observations

The results are validated on an Intel(R) Core i5 CPU running at 2.40GHz with 4.00GB of RAM. Software used for validation of the approach is MATLAB R2012a on a MS Windows 7 64-bit operating environment.The results of the denoising obtained for the T1 weighted, T2 weighted and PD axial images corrupted by spatially homogeneous and nonhomogeneous Gaussian and Rician noise from 3 to 12% noise levels are shown in Figs. 2–5. The experimental results have demonstrated the superior performance of the approach in terms of quantitative and qualitative evaluations.

The Fig.2 shows T1-w contrast enhanced image corrupted by 9% homogeneous Gaussian noise. Top row left: Original contrast enhanced image; Right: Corrupted by 9% homogeneous Gaussian noise; Middle row left: ADF approach; Right: Proposed NLM approach; Bottom row left: Residual of ADF; Right: Residual of NLM.

The Fig.3 shows T2-w contrast enhanced image corrupted by 7% non homogeneous Gaussian noise. Top row left: Original contrast enhanced image; Right: Corrupted by 7% non-homogeneous Gaussian noise; Middle row left: ADF approach; Right: Proposed NLM approach; Bottom row left: Residual of ADF; Right: Residual of NLM.

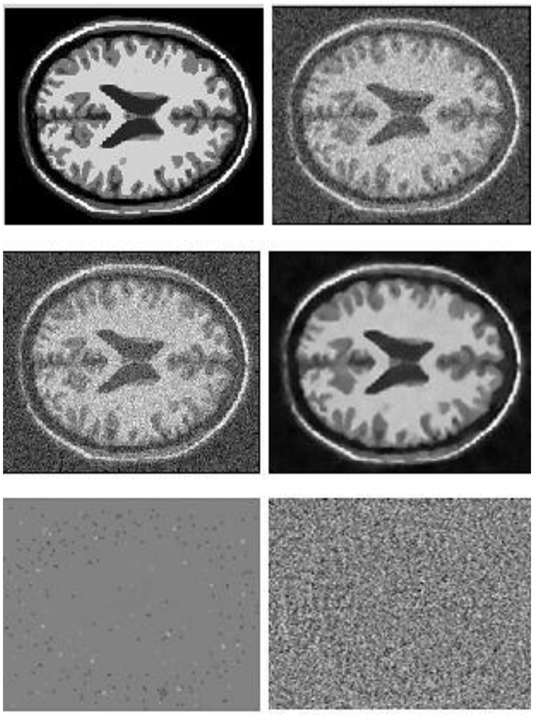

Fig.2 Validation with homogeneous Gaussian noise

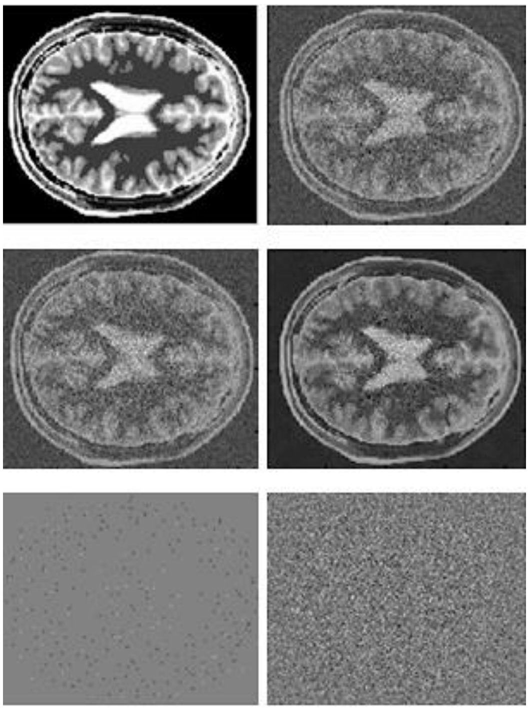

Fig.3 Validation with non homogeneous Gaussian noise

The Fig.4 shows PD contrast enhanced image corrupted by 9% homogeneous Rician noise. Top row left: Original contrast enhanced image; Right: Corrupted by 9% homogeneous Rician noise; Middle row left: ADF approach; Center: NLM approach; Right: Proposed UNLM approach; Bottom row left: Residual of ADF; Center: Residual of NLM approach; Right: Residual of UNLM approach.

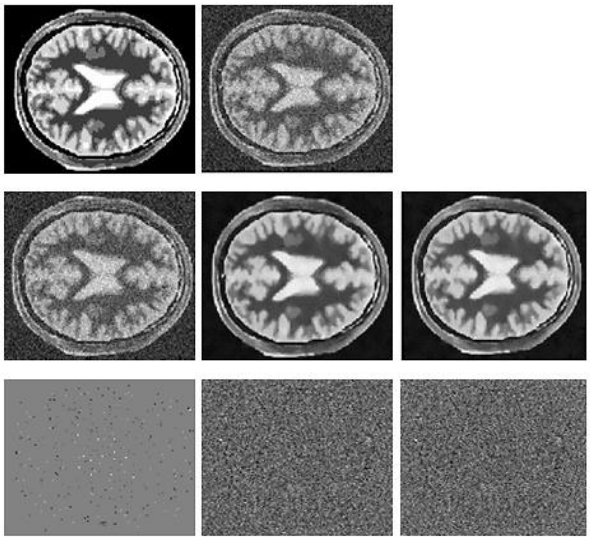

Fig.4 Validation with homogeneous Rician noise

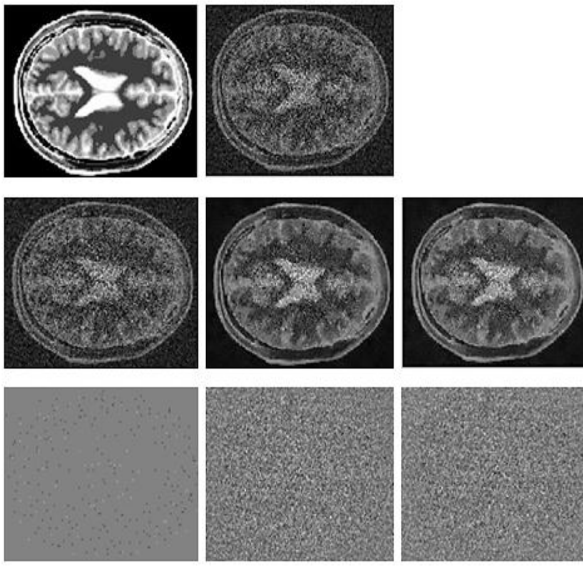

Fig.5 Validation with non homogeneous Rician noise

The Fig.5 shows T2-w contrast enhanced image corrupted by 11% non homogeneous Rician noise. Top row left: Original contrast enhanced image; Right: Corrupted by 11% nonhomogeneous Rician noise; Middle row left: ADF approach; Center: NLM approach; Right: Proposed UNLM approach; Bottom row left: Residual of ADF; Center: Residual of NLM approach; Right: Residual of UNLM approach.

The performance of the approach is also validated on three different clinical real T1w images with slice thickness of 5mm.Figure below shows a real image corrupted with 5% homogeneous Gaussian noise.

From the visual comparison of these results, the proposed method surpassed the ADF at high noise levels on the synthetic and real data in terms of producing a more detailed denoised image in which all the distinct features and small structural details are well preserved. The performance measures obtained for the T1 weighted,T2 weighted and PD axial images with different noise levels are given in Table 1- 4.The table 5 shows the average performance metrics for three sets of real images corrupted by 5% homogeneous Gaussian noise.

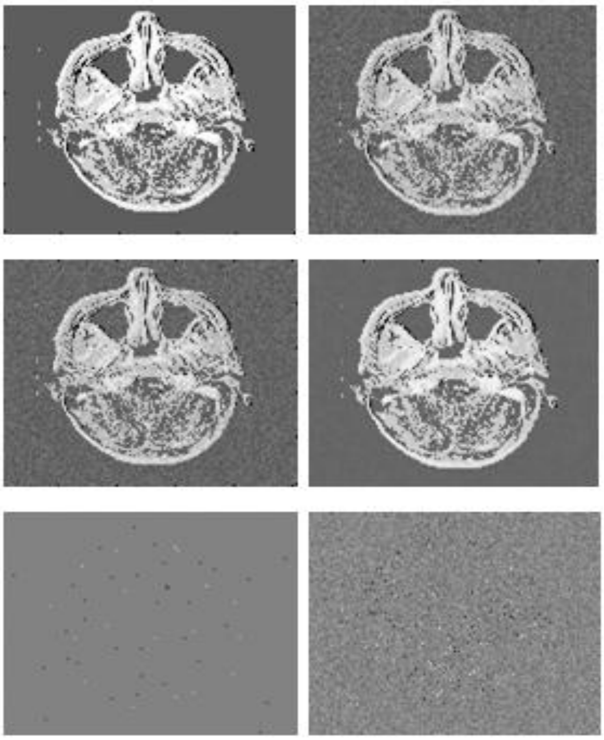

Fig.6 Validation with homogeneous Gaussian noise

Table 1 Comparison based on performance metrics for T1w image corrupted by 9% homogeneous Gaussian noise.

Method	MSE	RMSE	PSNR	SSIM
ADF approach	3.4624	5.8842	20.9357	0.5005
NLM approach	0.4781	2.1866	29.5340	0.6505

Table 2 Comparison based on performance metrics for T2w image corrupted by 7% non homogeneous Gaussian noise

Method	MSE	RMSE	PSNR	SSIM
ADF approach	8.0570	8.9766	17.2678	0.4600
NLM approach	2.4653	4.9651	22.4108	0.5823

Table 3 Comparison based on performance metrics for PD image corrupted by 9% homogeneous Rician noise

Method	MSE	RMSE	PSNR	SSIM
ADF	3.4179	5.8463	20.9918	0.5854
NLM approach	0.7641	2.7643	27.4979	0.6923
UNLM approach	0.7630	2.7622	27.5044	0.6945

Table 4 Comparison based on performance metrics for T2w image corrupted by 11% non homogeneous Rician noise

Method	MSE	RMSE	PSNR	SSIM
ADF	18.614	13.643	13.6311	0.3368
NLM approach	5.5058	7.4201	18.9213	0.4854
UNLM approach	5.0265	7.0898	19.3168	0.4861

Table 5 Average performance metrics for three real images corrupted by 5% homogeneous Gaussian noise.

Method	MSE	RMSE	PSNR	SSIM
ADF approach	1.072	3.273	26.0306	0.3632
NLM approach	0.4068	2.0158	30.2453	0.3689

As the level of noise increase, the performance of the proposed NLM filter shows significant improvement over the other denoising methods. Higher the value of PSNR and higher the value of SSIM shows that the proposed filter performs superior than the other denoising methods.

Conclusions and Future Scope

In this paper, an MRI enhancement technique based on histogram equalization and NLM has been suggested. Both homogeneous and spatially non-homogeneous Rician and Gaussian noise distributions with different levels have been added to the images.The performance of the proposed approach is compared with ADF based on MSE,RMSE,PSNR, and SSIM. The NLM filter with bias correction(UNLM) outperforms the NLM filter without bias in case of the Rician noise.The results demonstrate that the proposed approach can remove noise effectively not only in terms of visual perception, but also in terms of the quality metrics. This approach minimizes noise, while retaining local information of small structures. Almost no anatomical information can be noticed in the image residuals which ensures that all the distinct features and small structures are well-preserved. The future work includes extension to this approach to evaluate the improvement of the approach as a preprocessing step to other image processing techniques like brain tumor segmentation and registration. The current implementation by NLM performs well for images corrupted by both Gaussian and Rician noise, but the computational complexity is high, as it requires a large number of elementary operations for denoising of each pixel. It is given as $O(QRM)$ where Q is the number of pixels in the image, R and M are the number of pixels in the search and similarity window, respectively. The computational complexity of the approach can be brought down by performing dimensionality reduction.

References

J. R. Maclaren, (2008), Motion Detection and Correction in Magnetic Resonance Imaging, *University of Canterbury.*

E. J. Blink, (2004), Basics MRI Physics, *Medical Science Series.*

Hakon Gudbjartsson, Samuel Partz, (1995), The Rician distribution of noisy MRI data, *William and Wilkins,* pp.910-914.

Robert. D.Nowak, (1999), Wavelet-based rician noise removal in magnetic resonance imaging, *IEEE Transactions on Image Processing*, Vol. 8, pp. 1408-1419.

R. Garg, B. Mittal, S. Garg, (2011), Histogram Equalization techniques for image enhancement, *IJECT*, Vol. 2, pp. 107-111.

M. Kaur, J. Kaur, J. Kaur, (2011), Survey of contrast enhancement techniques based on histogram equalization, *International Journal of Advanced Computer Science and Applications*, Vol. 2.

G. Gerig, O. Kubler, R. Kikinis, F. A. Jolesz, (1992), Nonlinear anisotropic filtering of MRI data, *IEEE Transactions on Medical Imaging*, Vol. 2, pp.221-232.

K. Krissian S. Aja-Fernndez, (2009), Noise-driven anisotropic diffusion filtering of MRI, *IEEE Transactions on Image Processing*, Vol. 18, pp. 2265-2274.

L. Rudin, S. Osher, E. Fatemi, (1992), Nonlinear total variation based noise removal algorithms, *Physica D,* Vol. 60, pp. 259-268.

W. Guo, F. Huang, (2009), Adaptive total variation based filtering for MRI images with spatially inhomogeneous noise and artifacts, *IEEE Biomedical Imaging*.

J. Mohana, V. Krishnaveni, Y. Guo,(2014), A survey on the magnetic resonance image denoising methods, *Biomedical Signal Processing and Control*, Vol. 9, pp. 56-69.

A. Buades, B. Coll, J. Morel, (2005), A review of image denoising algorithms, with a new one, *Multiscale Model. Simul.*, Vol. 4, pp. 490-530.

J. Manjon, J. Carbonell-Caballero, J. Lull, G. Garca-Mart, L. Mart-Bonmat, M. Robles, (2008), MRI denoising using non-local means, *Med. Image Analalysis*, Vol. 12, pp. 514-523.

J. V. Manjon, P. Coupe, L. Marti-Bonmatic, D. L. Collinsb, M. Roblesa,(2010), Adaptive non-local means denoising of MR images with spatially varying noise levels, *Magnetic Resonance Imaging*, Vol. 31, pp. 192-203.

P. Coupe, P. Yger, S. Prima, P. Hellier, C. Kervrann, C. Barillot, (2008), An optimized blockwise Nonlocal Means denoising filter for 3-D magnetic resonance images, *IEEE Transactions on Medical Imaging*, Vol. 27, pp. 425-441.

M. Zhou Wang, A. C. Bovik, H. R. Sheikh, E. P. Simoncell, (2004), Image quality assessment: From error visibility to structural similarity, *IEEE Transactions on Image Processing*, Vol. 8, pp. 1-14.