Advances in Computer Science and Information Technology (ACSIT)
Print ISSN: 2393-9907; Online ISSN: 2393-9915; Volume 2, Number 11; April-June, 2015 pp. 20-24

http://www.krishisanskriti.org/acsit.html

Hybridization of Non Linear Algorithms in MR Images

Priyanka Punhani[1] and Naresh Kumar Garg[2]

[1]*Student at Dept. of Computer Science, GZS PTU Campus, Bathinda*
[2]*CSE Department, GZS, PTU Campus, Bathinda*
E-mail: [1]punhanipriyanka@gmail.com, [2]naresh2834@rediffmail.com

Abstract—*Magnetic Resonance Imaging (MRI) is most popularly used techniques in medical imaging. There are various non linear algorithms available to remove rician noise in images.The main aim of each filter is to preserve qualitative data of image. In literature, existing algorithms were not achieving the goal of preserving fine details and edges simultaneously. UNLM conserve most of details and ADF conserves edges. So the idea is to combine both the technique to take advantage of both simultaneously. The proposed method preserves both edges and details simultaneously irrespective of level of noise present on images.*

Keywords*: ADF, UNLM ,Bilateral Filtering, Weiner Filtering, MRI etc.*

1. INTRODUCTION

Magnetic Resonance Imaging (MRI) plays a very important role in medical imaging. It extracts fine details of tissues and organs and further use for clinical purposes. Tissues are differentiated based on their physical and biochemical properties. It has an advantage to produces sectional images of equal resolution in any plane without moving the patients. During acquisition process, addition of certain noise and artifacts reduces its image quality. It causes difficultyto analyzer to extract qualitative features from noisy image. There are two ways to reduce noise. One is to find data several times and average them [7]. This method makes data finding iterative in nature, which leads to increase in acquisition time. Second method is to apply post processing methods.

MR works on principle of Nuclear magnetic resonance (NMR). According to NMR, nuclei show some specific characteristics when placed under magnetic field. The human body is made up of water and fat molecules. Each water molecules contain 2 hydrogen molecules. Each hydrogen molecules contain some protons and a nucleus. These protons are analyzed for pathological and psychological aspects of tissues. When hydrogen atom is placed in magnetic field, its nuclei align itself in direction perpendicular to its field applied. When magnetic field is removed, nuclei realign itself at normal position. This generate RF signal at resonance frequency. Frequency and phase data of these signals are collected in k-space. The main limitation is acquisition time. To reduce it, it scans k-space faster. The k-space has an advantage of increase in acquisition speed.

In literature, there are various Liner and Non Linear filters available to remove noise from MR images. All the filters are aim towards removing noise while preserving edges and finer details of image. Median Filter is known as bench mark Filter. But due to its disadvantage of blurring image, it is less preferred. Perona and Malik [2] introducededge detection and scale space using Anisotropic Diffusion Filter (ADF). This Filter has an advantage of preserving most of edges. ADF has its own limitations that it usually erases small features and also adds staircase effect to denoised images. C. Tomasi and R. Manduchi [3] introduce Bilateral Filtering to smooth edges while preserving edges. This Filter combines gray levels and colors based on their geometric closeness and photometric similarity. The main limitation of this filter is that it doesn't preserve small structures in image and remove it by considering as noise. Jose V Manjón [6] proposed a parameterized filter named as Non Local Means (NLM). This filter is highly dependent on setting of its parameters. The main difference of NLM with other technique is that similarity is based on region comparison rather than pixel comparison. The main disadvantage of this filter is its computational burden. This filter doesn't removes Rician noise from image, so NLM is extended to Unbiased Non local Mean Filter (UNLM). UNLM preserves most of noise in image while attaining its contrast level. Among all existing filters were not achieving the goal of noise removal simultaneously. So there is need for an algorithm to achieve the goal of edges and feature preservation simultaneously. As it is analyzed from literature that UNLM preserve features and contrast of image, while ADF preserve edges in image. So the idea is to combine these best two algorithm to attain the goal. The proposed algorithm modifies existing ADF and UNLM, and combines them. It shows better results at lower level of noise. The proposed algorithm works towards a common goal of preserving features and edges in image.

2. NON-LINEAR DENOISING FILTERS

There are various non linear algorithms available in literature to remove rician noise from images. It is analyzed that UNLM and Anisotropic Diffusion Filter (ADF) performs well at all level of noise. As discussed in above section, UNLM preserves the finer details and contrast level of image while ADF preserves edges in image. So both the existing techniques are selected to combine and create a new algorithm. Various other combinations of UNLM with Bilateral Filter, Wiener Filter, and Median Filter are tested. The combination of modified UNLM and Anisotropic Diffusion Filter (ADF) gives better results. This section explains the existing UNLM and ADF algorithm along with proposed algorithm.

2.1 Anisotropic Diffusion Filter (ADF)

Perona and Malik (1990) [2] introduce scale space and edge detection using Anisotropic Diffusion technique. At coarser resolution, it is difficult to obtain semantically meaningful edges. This filter provides intra region filtering rather than inter region filtering. The main idea behind this approach is to convolve original image $I_0(x,y)$with Gaussian filter $G(x,y;t)$of variance t

$$I(x,y,t) = I_0(x,y) * G(x,y;t) \quad (1)$$

It is based on heat equation with initial condition, $I(x,y,0) = I_0(x,y)$.Here anisotropic diffusion equation is defined as

$$I_t = div(c(x,y,t)\nabla I) = c(x,y,t)\Delta I + \nabla c \cdot \nabla I \quad (2)$$

Where *div* is divergence operator, ∇ is gradient operator, Δis Laplacian operator with respect to space. It is reduces to heat equation$I_t = c\Delta I$, if $c(x,y,t)$ is a constant [5]. If we want tosmoothening with in edges rather than across at boundaries. This is done by setting conduction coefficient 1 at region, and 0 at boundaries.To test anisotropic diffusion filter numerically, 4 nearest neighbor discretization of Laplacian operator can be used.

$$I_{i,j}^{t+1} = I_{i,j}^{t} + \lambda[C_N.\nabla_N I + C_S.\nabla_S I + C_E.\nabla_E I + C_W.\nabla_W I]_{i,j}^{t} \quad (3)$$

where 0 <λ< ¼, and N, S, E, W are mnemonics for North, South, East and West respectively.∇ Indicates nearest-neighbor difference as

$$\nabla_N I_{i,j} \equiv I_{i-1,j} - I_{i,j} \quad (4)$$

$$\nabla_S I_{i,j} \equiv I_{i+1,j} - I_{i,j} \quad (5)$$

$$\nabla_E I_{i,j} \equiv I_{i,j+1} - I_{i,j} \quad (6)$$

$$\nabla_W I_{i,j} \equiv I_{i,j-1} - I_{i,j} \quad (7)$$

The conduction coefficient is defined as norm of gradient at each arc location with absolute value of its projection along direction of arc:

$$C_{N_{i,j}}^{t} = g(|\nabla_N I_{i,j}^{t}|) \quad (8)$$

$$C_{S_{i,j}}^{t} = g(|\nabla_S I_{i,j}^{t}|) \quad (9)$$

$$C_{E_{i,j}}^{t} = g(|\nabla_E I_{i,j}^{t}|) \quad (10)$$

$$C_{W_{i,j}}^{t} = g(|\nabla_W I_{i,j}^{t}|) \quad (11)$$

The final image is obtained using $g(.)$for different scale-space. For high contrast edges over low-contrast, $g(.)$ is defined as

$$g(\nabla I) = e^{(-(||\nabla I||/K)^2)} \quad (12)$$

For wide regions over small ones, $g(.)$ is defined as

$$g(\nabla I) = \frac{1}{1 + (\frac{||\nabla I||}{K})^2} \quad (13)$$

The value of K is set to a fixed value or to the 90% value of its integral at every iteration.

Unbiased Non Local Mean (UNLM)

Buades et al [4] proposed a parameterized filter named as Non Local Means (NLM). This filter is highly dependent on setting of its parameters. This filter is based on yaroslavsky filter which averages the similar image pixel based on intensity distance. The main difference of NLM with other technique is that similarity is based on region comparison rather than pixel comparison.

Numerically NLM method is used to calculate weighted average of all pixels in the image by using following formula:

$$NLM(Y(p)) = \sum_{\forall q \in Y} w(p,q)Y(q),$$
$$0 \le w(p,q) \le 1 \sum_{\forall q \in Y} w(p,q) = 1 \quad (14)$$

where p defines pixel to be filtered and q defines each pixel in image. The similarity between neighborhoods N_p and N_q defines the weights $W(p,q)$. A square neighborhood with center around pixel i is defined by N_i having user defined radiusR_{sim} . The similarity is defined by

$$w(p,q) = \frac{1}{Z(p)} e^{-\frac{d(p,q)}{h^2}} \quad (15)$$

$$Z(p) = \sum_{\forall q} e^{-\frac{d(p,q)}{h^2}} \quad (16)$$

where$Z(p), h, d$ defines normalization constant, exponential decay, and Gaussian weighted Euclidian distance respectively. Gaussian weighted Euclidian distance is calculated using a formula:

$$d(p,q) = G_p ||Y(N_p) - Y(N_q)||^2 R_{sim} \quad (17)$$

whereG_p is normalized gaussian function having zero mean and ρ is standard deviation that is usually set to 1.

There is a special case when p=q, it produces an over weighted effect to solve this problem Gaussian weighted Euclidian distance is calculated using a formula:

$$w(p,q) = \max(w(p,q)\ \forall q \ne p \quad (18)$$

There a problem exists that in magnitude of MR images id defined as thesquare root of sum of square of gaussian distributed real and imaginary part, it follows Rician distribution [6]. But in case of low intensity region it tends to Raleigh distribution while in case of high region intensity it tends to Gaussian distribution. Due to this image contrast is reduced.

This problem is overcome by filtering square of MRI magnitude images; Unbiased NLM (UNLM) is defined as**:**

$$UNLM(Y) = \sqrt{NLM(Y)^2 - 2\sigma^2} \quad (19)$$

σ Is calculated using Otsu's threshold method where $\sigma = \sqrt{\frac{\mu}{2}}$, where μ is mean value of the squared magnitude image. This method computes bias in image which is equal to$2\sigma^2$. Fist we calculate mean, using Otsu's threshold and then calculate $2\sigma^2$ to compute UNLM [5].

Proposed Algorithm

The proposed work is done to attain the goal of preserving the edges and minute details in image simultaneously. Among all the existing algorithms, best 2 algorithms i.e. UNLM and Anisotropic Diffusion Filter (ADF) are selected to combine.
In proposed work, image filtered by UNLM is passed to ADF as an input image. The UNLM and ADF algorithms are modified to attain better results in output.

The existing UNLM calculates bias by using Otsu's thresholding method. The proposed method calculates bias by using new method of bias estimation proposed by Santiago Aja-Fernandez [8]

$$\sigma_n = \sqrt{\frac{2}{\pi}} mode(\hat{u_{2}}_{ij}), \hat{u_{1}}_{ij} = \frac{1}{|n_{ij}|-1} \sum_{p \in n_{ij}} I_p \quad (20)$$

Where $\hat{u_1}_{ij}$ calculates local statistics in image, and $\sigma_n$calculates bias present in image.
In existing ADF, input image is convolved with directional masks and its intensity value and conduction coefficient is calculated in different directions.

In proposed algorithm, input image is convolved with a well defined user mask and its intensity value and conduction coefficient is calculated in different directions as per explained by Perona and Malik in [2].

Numerically, the proposed work is defined as. The input image $I_0(x,y)$ is convolved by a well defined mask.

$$I(x,y) = I_0(x,y) * mask \quad (21)$$

Where a well defined user mask is defined as

$$mask = [1\ 1\ 1; 1\ 9\ 1; 1\ 1\ 1] \quad (22)$$

The intensity value and conduction coefficient is calculated by its gradient value for different scale space as explained by Perona and Malik [2].

3. EXPERIMENTS AND RESULTS

All the algorithms explained above are tested on two set of MR scanned brain image of size 181×181 with different

Rician noise level. These sets contain t1-weighted and pd-weighted images of different level of Rician noise such as 3%, 6%, 9%, 12% and 15%.Its performance is compared on the basis of Quality parameter i.e. PSNR (peak signal to noise Ratio) and SSIM (structural symmetric index metric) [1].

3.1 SSIM based Performance Analysis

Table 1: Showing values of SSIM for Various Non Linear Filters at different level of Rician noise.

Noise Level ↓ Filters →	t1=3%	t1=6%	t1=9%	t1=12%	t1=15%
UNLM	1	1	0.9995	0.9976	0.9955
Anisotropic	0.9999	0.9993	0.9983	0.9964	0.9948
Proposed	1	1	1	0.9996	0.9990

Table 1 shows the value of SSIM for different Rician noise level. From Table 1, it is analyzed that in comparison with UNLM and ADF, UNLM is showing highest value of output SSIM at all level of noise. UNLM preserves most of minute details at lower level of noise. As noise level increases, minute structure preserve by ADF is less. The proposed method preserves more structural detail than ADF and UNLM at all level of noise. At lower level of noise, proposed method preserves almost all of details and at higher level preserves most of detail as compared to UNLM.

3.2 PSNR value based performance Analysis:

Table 2: Showing values of PSNR for Various Non Linear Filters at different level of Rician noise.

Noise Level ↓ Filters →	*t*1=3%	*t*1=6%	*t*1=9%	*t*1=12%	*t*1=15%
UNLM	37.24	36.30	32.37	27.40	24.70
Anisotropic	36.03	31.23	27.87	25.53	23.33
Proposed	39.39	36.60	34.10	32.63	31.39

Table 2 shows value of PSNR for different level of MR scanned brain image with different level of Rician noise. As analyzed from Table 2, UNLM is giving higher value of PSNR than ADF at all level of noise. The value of PSNR is decreased as noise level increases. The proposed method gives better PSNR value than ADF and UNLM at all level of noise. The noise removing capability of proposed method increases with increase in noise level of image.

3.3 Visual Analysis based on denoised images obtained after applying various filtering techniques:

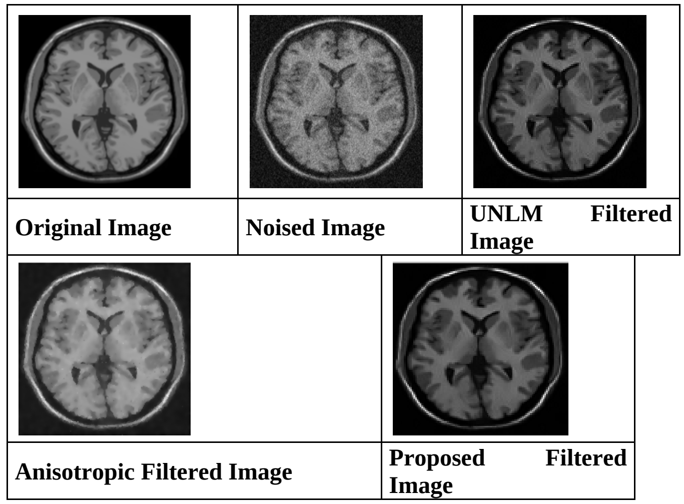

Fig. 1: Filtered scanned Brain MR Images with noise level of 12%

Fig. 1 shows filteredscanned Brain MR Images with noise level 12% of image intensity. As it is analyzed from above figure,UNLM is preserving minute structural details and contrast level of image as compared to ADF. The Anisotropic Diffusion Filter (ADF) preserves edges in image. The proposed method combines the advantage of both the filter and gives better results. Image filtered by proposed method gives visually better results than both UNLM and ADF.

4. CONCLUSION

In literature, there are several non linear filters available to remove rician noise from MR images. The main goal of the entire filter is to remove noise and to preserve structural details from image simultaneously. But none of existing filters achieve this goal at same time. As it is analyzed, UNLM is preserving most of the structural details and contrast level of image. ADF is preserving edges in image. So the proposed method is designed to achieve the goal simultaneously. The proposed method works well than existing UNLM and ADF at all level of noise. It gives improved PSNR and SSIM value at different level of noise. It preserves most of structural detail and removes most of noise as compared to existing algorithms irrespective of noise level of image.

REFERENCES

[1] Rafael C. Gonzalez, Richard E. Woods, “Digital Image Processing”, Pearson publication, Third edition.

[2] Pietro Perona, Jitendra Malik, “Scale space and Edge Detection using Anisotropic Diffusion”, IEEE transaction on pattern analysis and Machine intelligence, Vol. 12, No. 7, 1990, pp. 629-639.

[3] C. Tomasi, R. Manduchi, “Bilateral Filtering for Gray and Color Image”, IEEE international Conference on Computer Vision, 1998, pp. 1-8.

[4] A. Buades, B. Coll, J.M. Morel, “A review of image denoising algorithms, with a new one”, Multiscale Model. Simul. 4, 2005, pp. 490–530.

[5] J. Tang, Q. Sun, J. Liu, Y. Cao, “An adaptive anisotropic diffusion filter for noise reduction in MR images”, in: Proceedings of IEEE International Conference on Mechatronics and Automation, Harbin, China, 2007, pp. 1299–1304.

[6] J.V. Manjón, J. Carbonell-Caballero, J.J. Lull, G. García-Martí, L. Martí-Bonmatí,M. Robles,” MRI denoising using non-local means”, Med. Image Anal. 12, 2008, pp.514–523.

[7] J. Mohan, V. Krishnaveni, Yanhui Guo A, “Survey on the magnetic resonance image denoising methods”, Biomedical Signal Processing and Control 9, 2014, pp. 56– 69.

[8] Santiago Aja-Fernández, Carlos Alberola-López, and Carl-Fredrik Westin, “Noise and Signal Estimation in magnitude MRI and Rician Distributed Images: A LMMSE Approach”, IEEE Transactions on Image Processing 17, 2008, pp.1383-1398.