Research Article

Improved Fuzzy Based Non-Local Mean Filter to Denoise Rician Noise

Devinder Singh [1] and Amandeep Kaur [2]
[1] Department of Computer Science, Mata Gujri College, Fatehgarh Sahib, India
devinder78@yahoo.co.in
[2] Department of Computer Science and Technology, Central University of Punjab, Bathinda, India

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Abstract.: Nowadays MRI has become an important tool to diagnose medical conditions but there is a growing need for a denoise image produced. Rician noise is one of the major challenges in MRI. So the nonlocal means (NLM) filter has gained popularity to denoise medical images as it gives excellent results. In the present work, an Improved Fuzzy-based Non-Local Mean Filter is proposed for denoise Rician noise. In the proposed method the first step is to find the non-local similar pixel in the image using fuzzy function. Then these similar pixels are used to generate noise-free pixels. The above approach is tested with real data and the results are compared with existing Fuzzy techniques by using root mean square error, structural similarity index measure, and peak signal-noise ratio (PSNR) methods. This technique gives better result than the existing Fuzzy Non-Local Mean technique with both high and low-density Rician noise in the image

Keywords: Image denoising, Fuzzy logic, Rician Noise.

1 INTRODUCTION

MRI images are used in the medical field to diagnose various kinds of diseases in the human body. With the advancement of computerized image processing, the digital image processing field has become one of the core areas of research. The advancement of new technologies for digital image processing, MRI, CT scan, Ultrasound, and digital X-ray gave a new impetus to medical sciences. Using these technologies, doctors can easily diagnose the patient's problem without any biopsy test. To make use of these technologies, doctors require good quality, sharp and clear digital images for proper diagnosis. Most of these medical images suffer from one or another kind of noise. Noise blurs the important features in the images. Thus, noise suppression is the most challenging aspect in the development of computerized medical technology and also for manual analysis of these medical images by medical practitioners.

1.1 Noise

There are two types of noise, additive noise, and multiplicative noise. If $g(m,n)$ is the original image, $g'(m,n)$ degraded image and $\eta(m,n)$ be the noise function, then additive noise is $g'(m,n) = g(m,n) + \eta(m,n)$. Additive noise does not depend upon the pixel values of the original image. Uniform, Gaussian Noise, and Impulse noise are additive types. Multiplicative noise depends upon signal and its magnitude is related to the original pixel value as given by $g'(m,n) = g(m,n) + \eta(m,n)\, g(m,n)$ Speckle noise and Rician noise are multiplicative noises [1, 2].

1.2 Rician Noise in MRI Images

Rician noise mainly arises from complex Gaussian noise and degrades the MRI images. The Rician noise is a combination of additive and multiplicative noise [3]. In the medical field, quick and clear images are required for diagnosis. In MRI, noise can be reduced by averaging multiple acquisition images. But speed plays a major role in diagnosis. Thus, instead of acquiring multiple MRI images, different post-processing methods can be applied to denoise these.

1.3 Rician Noise Suppression

It is easy to remove the additive noise as compared to Rician noise. Since that Rician noise depends upon the signal so it is very difficult or challenging to separate noise from the signal which is not the case with additive Gaussian noise. Rician noise becomes a major problem particularly for the low signal-to-noise ratio(SNR) range and it results in additional signal-dependent bias in the data along with random fluctuation resulting in reduced image contrast. There are different denoising methods introduced by different researchers such as nonlocal maximum likelihood (NLML) [5] estimation method, wavelet-domain filtering method [4] for Rician noise reduction, NLM is a promising method initially developed to suppress Gaussian noise. NLM was introduced by A. Buades [8]. The main drawback of traditional NLM is its slow speed. Various researchers have worked to optimize its speed [12, 13, 14, 15]. Different researchers have proposed various modifications to improve its performance for other types of noises (speckle, rician). The NLM is generally modified to suppress rician noise by adding a bias term [5, 7, 9, 10]. Other researchers have changed NLM methods for Rician noise suppression using soft computing techniques. The genetic programming (GP)-based approach does not require any prior information regarding noise variance [6]. To remove the Rician noise, the NLM method eliminates high-frequency signal components while blurring the edges, and resulting in adding extra bias in the quantification process. To overcome these draw-backs, an advanced image restoration approach is required. For MRI images having a low level of Rician noise, a Non-local statistical filter yields better results particularly in non-smooth regions, and for high-level Rician noise images and smooth regions, the local statistical filter performs better. To remove this drawback Fuzzy based hybrid filter has been proposed [16]. Nowadays to denoise Rician noises, Impulse noise new Fuzzy based filters are introduced [11, 15, 17, 18, 19, 20]. Mainly two types of methods are proposed in the literature to denoise Rician noise. The first approach relies on estimating the image intensity function $m(x,y)$ derived from the model by assessing the functional relation between $m(x,y)$ and $Z(x,y)$. The second approach uses the conventional denoising method and the bias is suppressed using the post-processing method [17-20]. Aja-Fernandez et al [22] proposed a simple bias subtraction method.

$$m(x,y)=\sqrt{m_1(x,y)-2\sigma^2} \tag{1}$$

In which $m(x,y)$ is the unbiased value and $m_1(x,y)$ which is obtained after applying the conventional de-noising methods to the Rician noise corrupted image.

2 PROPOSED METHOD

The present work used Fuzzy similarity-based Non Local Mean as a base to denoise Rician noise from the image. Whereas in the present work parameter less Fuzzy filter is used to find the similarity between the windows instead of using a trapezoidal function.

Step 1: Let $E(m,n)$ be an input Image, here E is the intensity at the coordinate position (m,n).

Step 2: Padding the input image $E(m,n)$.

Padding size: $w_p=\left(\frac{w+1}{2}-1\right)$

Where, w is size of window. After padding size of image became

$m=m+2*w_p$

$n=n+2*w_p$

Initialize *xpix=1*

Step 3: $for \quad i=1 \quad to \quad m \ do$

Initialize y*pix=1*

Step 4: $for \quad j=1 \quad to \quad n \quad do$

$initialize \quad w_i=0$

Step 5: Let t be a window of a size $w\times w$ that is used to search similar patches around the central pixel.

$for \quad u=i \quad to \quad w+i-1 \quad do$

$w_i=w_i+1$

$initialize \quad w_j=0$

$for \quad v=j \quad to \quad w+j-1$

$w_j=w_j+1$

$t(w_i,w_j)=E(u,v)$

$end \ for$

$end \ for$

Step 6: Let z be a local window of size $R\times R$ in the window *t*. The Centre of both windows *z* and *t* is the same.

$for \quad g=in \quad to \quad op$

$for \quad h=in \quad to \quad op$

$z(g,h)=t(g,h)$

end

end

$$where, \quad in=\left(\left(\frac{w+1}{2}\right)-\left(\frac{R-1}{2}\right)\right) and \quad op=\left(\left(\frac{w+1}{2}\right)+\left(\frac{R-1}{2}\right)\right)$$

Step 7: k be a non-local window of a size $R\times R$ that is taken from the window *t*.

$initialize \quad e1=1, sum=0, \quad tr=0$

$for \quad o=1 \quad to \quad w-2.$

$for \quad p = 1 \quad to \quad w-2$
$initialize \quad q = 0$
$for \quad ml = o \quad to \quad (o+R)-1$
$q = q+1 \quad initialize \quad r = 0$
$for \quad nl = p \quad to \quad (p+R)-1$
$r = r+1$
$k(q,r) = t(ml,nl)$
$end\ for$
$end\ for$

Step 8: Find the mean μ_l of local window z and μ_n mean of non-local window k

$$\mu_l = \sum_{im=1}^{R} \sum_{jm=1}^{R} z(im, jm) \Big/ R \times R \qquad (2)$$

$$\mu_n = \sum_{am=1}^{R} \sum_{bm=1}^{R} k(am, bm) \Big/ R \times R \qquad (3)$$

Step 9: Find the ratio of Mean μ_l of Local window z and mean μ_n of non-local window k.

$if\ \mu_l < \mu_n$

$$Ratio_\mu = \frac{\mu_l}{\mu_n}$$

$else$

$$Ratio_\mu = \frac{\mu_n}{\mu_l}$$

end

Step 10: Find the standard deviation σ_l of local window z and σ_n standard deviation of non-local window k

$$\sigma_l = \sqrt{\frac{\sum z^2}{N} - \mu_l}$$
$$\sigma_n = \sqrt{\frac{\sum z^2}{N} - \mu_n} \qquad (4)$$

Step 11: Find the ratio of the standard deviation σ_l of local window z and σ_n standard deviation of nonlocal window k

$if\ \sigma_l < \sigma_n$

$$Ratio_\sigma = \frac{\sigma_l}{\sigma_n}$$

$else$

$$Ratio_\sigma = \frac{\sigma_n}{\sigma_l}$$

end

Step 12: After finding the $Ratio_\mu$ and $Ratio_\sigma$, set the similarity threshold sim_t to 0.5 and compare with $Ratio_\mu$ and $Ratio_\sigma$. If $Ratio_\mu \geq sim_t$ and $Ratio_\sigma \geq sim_t$ that mean local window z are similar with k else not.

Step 13: After finding the similar windows which are used to generate noise-free pixel. Weights of similar windows are calculated by finding Euclidean distance from the non-local similar and local window, if Euclidean distance is lower then the window contributes more towards an estimate of the noise-free pixel otherwise less contribution.

To calculate the weight of all non-local windows

$$weight_{nl} = e^{-\frac{(d-\mu)^2}{2\sigma^2}} \qquad (5)$$

$$d = \|z-k\| \qquad (6)$$

d is Euclidean distance of local window *z* from non-local window *k*.
Based on the calculated weight the denoised pixel is given by

$$pixel \ = \frac{1}{\sum_{nl=1}^{Y} weight_{nl}} \sum_{nl=1}^{Y} (pixel_{nl} \times weight_{nl}) \qquad (7)$$

$pixel$ is a denoised pixel and Y gives the number of non-local similar windows and local window, $pixel_{nl}$ is non-local window central pixel and $weight_{nl}$ is the weight calculated for those windows.

end for Step 7
end for Step7
F(xpix,ypix)=pixel
ypix=ypix+1
end for Step 4
Xpix=xpix+1
end for Step3

Step 14: Then Final image is generated by bias correction using equation (1).

$$out(x, y) = \sqrt{F(x, y) - 2sigma^2} \qquad (8)$$

sigma is standard deviation found using the noise estimation technique defined in the paper[22].

3 DATA SET AND QUANTITATIVE METRICS

The experiment is performed on Real data set. To check the performance of the proposed work different quantitative techniques such as PSNR, MSE and MSSIM are used.

3.1 Data Set

Six different MRI images were selected for the experiment. Real data is downloaded from BrainWeb [21]. The file format of MRI images used for testing is tiff and size 181x181. These images are used to check the performance of the proposed work and compare it with existing techniques.

3.2 Assessment Parameters

To quantify the performance of the proposed method PSNR, MSE, and MSSIM quantitative techniques are used.

Mean square error Let $I(a,b)$ is the original image and $f(a,b)$ is then filtered final image and mse of the both image is

$$mse(I(a,b)f(a,b)) = \frac{1}{n*m} \sum_{a=1}^{n} \sum_{b=1}^{m} (I(a,b) - f(a,b))^2 \qquad (9)$$

Peak Signal to Noise Ratio

$$PSNR(I(a,b)\, f(a,b)) = 10 * \log\left(\frac{G^2}{mse(I(a,b)\, f(a,b))} \right) \qquad (10)$$

G represents the gray level of the image.

Structural Similarity index measure This is a method that is used to check the similarity between two images of the same size.

$$SSIM(a,b) = \frac{(2\mu_a \mu_b + c1)(2\sigma_{ab} + c2)}{(\mu_a^2 + \mu_b^2 + c1)(\sigma_a^2 + \sigma_b^2 + c2)} \qquad (11)$$

μ_a is the mean of image a, μ_b is the mean of image b
σ_a Variance of a
σ_b Variance of b
σ_{ab} covariance of a and b
$c1 = k_1 L \quad and \quad c2 = k_2 L$

where L is dynamic range and $k_1 = 0.01 \ \ k_2 = 0.03$

4 EXPERIMENTAL RESULTS

We implement the proposed method and the various existing methods in MatLab environment on a PC with Intel(R) Core 2Duo CPU and 3 GB RAM. The results are compared with an unbiased NLM filter (UNLM) [8] and a fuzzy NLM method [11] with bias correction. The performance of the three methods (UNLM, Fuzzy NLM, Proposed) is compared using T2, and PD weighted MRI images from BrainWeb phantom [21] with noise levels 6%, 9%, 12%. The original and noisy images with various noise levels are shown in Fig.1. The visual results after applying the four denoising methods are shown in Fig.1. Table-1 shows the MSE, PSNR, and MSSIM values. The visual results of both fuzzy-based methods look similar. The proposed method gives significantly better PSNR values than the other two values suggesting better suppression of noise. The MSSIM values shown in Table-1, reveal that the proposed method preserves the structural information in a better way than the two other methods.

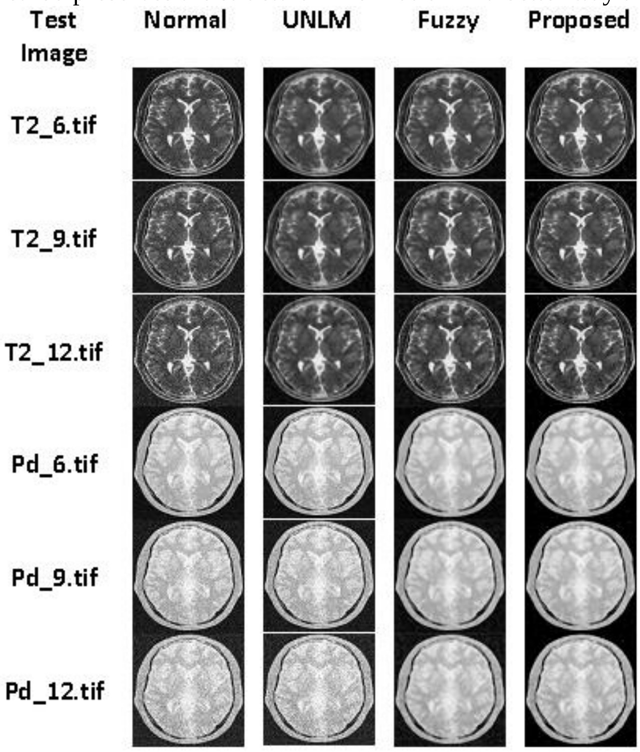

Fig. 1. a) Normal image b) Denoised image using UNLM d) Denoised image using FSNLM with trapezoidal membership function e) Denoised image using proposed method.

Table 1. Results in terms of PSNR, MSE and MSSIM

Test Image	Method	MSE	PSNR	MSSIM
T2_6.tif	Noise Image	289.68	23.51	0.5761
	UNLM	267.03	23.86	0.7241
	Fuzzy	132.36	26.91	0.7636
	Proposed	87.37	28.71	0.8062
T2_9.tif	Noise Image	598.71	20.36	0.4791
	UNLM	400.51	22.10	0.6520
	Fuzzy	211.11	24.88	0.6987
	Proposed	135.98	26.79	0.7400
T2_12.tif	Noise Image	1045.3	17.93	0.4106
	UNLM	451.52	21.58	0.6245
	Fuzzy	307.95	23.24	0.5761
	Proposed	236.86	24.47	0.7144
Pd_6.tif	Noise Image	278.68	23.69	0.4928
	UNLM	185.89	25.43	0.7109
	Fuzzy	146.91	26.46	0.7246
	Proposed	86.55	28.75	0.8380
Pd_9.tif	Noise Image	613.03	20.26	0.3759
	UNLM	250.65	24.14	0.6690
	Fuzzy	203.53	25.18	0.6710
	Proposed	111.23	27.67	0.7900
Pd_12.tif	Noise Image	1075.70	17.81	0.3031
	UNLM	337.31	22.85	0.6339
	Fuzzy	288.52	23.53	0.6205
	Proposed	147.70	26.44	0.7414

5 CONCLUSION AND FUTURE WORK

This paper proposes an improved denoising technique using an improved fuzzy NLM filter that is effective for Rician noise. The technique is computationally less complex than the existing fuzzy NLM-based similar techniques with improved denoising results.

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