A Comparative Analysis of Noise Reduction Filters in MRI Images

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Abstract - *Post inheritance denoising of magnetic resonance (MR) images is of emphatic for clinical diagnosis and computerized decisive test, such as tissue classification and segmentation. It has been exposed that when signal to noise ratio (SNR) is low, the noise in MR magnitude images follows a Rician distribution, which is signal dependent. It is particularly difficult to remove the random fluctuations and bias introduced by Rician noise. To analyze the noise free signal from MR magnitude images is the objective of this paper. We model images as random fields and predict that pixels which have similar burst adjacent to the same distribution. I have compared the NLML and Bilateral method for Rician noise reduction in MR images. We recommend a iterative bilateral filter (IBLF) estimation method for Rician noise reduction. This method returns an optimal estimation result that is more accurate in recovering the true signal from Rician noise than NLML means algorithm in the manner of SNR, contrast, and method error. We manifest that NLML performs better than the traditional local maximum likelihood (LML) estimation method in conserving and defining sharp tissue boundaries in terms of well-defined sharpness metric while also having superior performance in method error.*

Keywords: Denoising, magnetic resonance (MR) images, nonlocal maximum likelihood estimation (NLML), nonlocal (NL) means, Rician distribution.

1. INTRODUCTION

In magnetic resonance imaging (MRI), sources of noise generally include thermal effect, inductive losses, sample resolution, and field of- view [6], [5]. Due to the nature of the Gaussian noise in both real and imaginary parts of the k-space raw data, the spatial distribution of noise in MR magnitude images is usually modelled as a Rician distribution [10], [6]. In contrast to Gaussian noise, Rician noise is not zero mean with the mean dependent on the local intensity of the image. This unpleasant noise may influence the effectiveness of subsequent analyses, diagnoses, and treatments that rely on faithful anatomical data. Noise removal in MR images has been challenging and essential despite of significant advances in imaging techniques in recent years. It is of particularly importance in computerized post processing procedures such as tissue classification, segmentation, registration, and brain mapping. Over the decades, Gaussian low-pass filters have been widely used in many MR image processing applications for its simplicity [5]. In particular, it computes a weighted average of pixel values in the neighbourhood in such a way that the weight decreases with distance from the kernel centre. Though the Gaussian filters smoothes noise quite efficiently edges are blurred significantly. A nonlinear method used to Sustain the sharpness called the anisotropic diffusion filter [6] has been proposed. In their approach, pixel values are averaged from neighbour hoods, whose size and shape depend on local image variation that is measured at every point. The diffusion coefficient is chosen to be an appropriate function of the image gradient in such a way as to encourage tranquiling within a region in preference to smoothing across the boundaries. On the other hand, the bilateral filter [8] has been proposed based on the improvement of the Gaussian filter. The essence underlying this approach is to aggregate both geometric closeness in the spatial domain and gray value similarity in the range as a nonlinear filter for image denoising. It has been demonstrated that the bilateral filter performed effectively in MR image noise suppression.

1.1 Noise characteristics in MRI

The sovereign source of noise in MRI is thermal in origin which is originated by the stochastic motion of free electrons. The thermal noise is consulted to be white, additive and follows a Gaussian distribution with a variance σ and mean zero. So the acquire draw complex MR data in the presence of thermal noise in the k-space are delineate by a Gaussian probability density function (PDF). The k-space data is then Fourier transformed to retrieve the magnetization distribution. The distribution of data in the term of real and imaginary components will still be Gaussian due to the linearity and the orthogonality of the Fourier transform. However, the magnitude of the reconstructed MR image is commonly used for visual inspection as well as for automatic computer analysis. Since the magnitude reconstruction is commonly the square root of the sum of two independent Gaussian random variables, the magnitude image data are described by a Rician distribution [9]. Let 'R' and 'I' characterized the real and imaginary parts of the noisy complex MR data (corrupted with zero mean Gaussian, stationary noise with the standard deviation σ) with mean values μR and μI, respectively. Then the probability distribution function (PDF) of the magnitude data will be a Rician distribution, as described by

$$P_{\text{mag}}(M) = \frac{M}{\sigma^2} e^{-\frac{M^2+A^2}{2\sigma^2}} I_0\left(\frac{AM}{\sigma^2}\right), \quad M \geq 0 \quad (1)$$

Where $M = (R^2+I^2)^{1/2}$, $A = (\mu R^2 + \mu I^2)^{1/2}$

And I_0 is the modified Bessel function of the first kind with order zero. The first two moments of the Rice PDF are given below:

$$E[M] = \sigma\sqrt{\frac{\pi}{2}} e^{-\frac{A^2}{4\sigma^2}} \left[\left(1+\frac{A^2}{2\sigma^2}\right) I_0\left(\frac{A^2}{4\sigma^2}\right) + \frac{A^2}{2\sigma^2} I_1\left(\frac{A^2}{4\sigma^2}\right)\right] \quad (2)$$

$$E[M^2] = A^2 + 2\sigma^2 \quad (3)$$

The Rician distribution tends to be a Rayleigh distribution when the SNR goes to zero.

$$P_{\text{mag}}(M) = \frac{M}{\sigma^2} e^{-\frac{M^2}{2\sigma^2}}, \quad M \geq 0 \quad (4)$$

The Rician distribution tends to be a Gaussian distribution when SNR is high.

$$P_{\text{mag}}(M) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{\left(M-\sqrt{A^2+\sigma^2}\right)^2}{2\sigma^2}} \quad (5)$$

Therefore in regions which has low SNR on an MR image, the Rician distribution approach to bea Rayleigh distribution. In high SNR regions, it forces to be a Gaussian distribution. The shape of the Rician distribution lean on the SNR, which is here defined as the ratio A σ.

2. METHODS

We shall start by introducing the bilateral filter proposed by Tomasi and Manduchi.

2.1. NLML: (NON-LOCAL MAXIMUM LIKELIHOOD)

A non-local means (NLM) filter, which outputs a weighted average of pixels in a relatively large search window and assigns high weights to pixels with similar neighbouring patterns, recently exhibits capability to preserve details and suppress Gaussian distributed noise as well. Generally Rician Noise is follows as noise in magnitude of MR images.

2.2. Bilateral Filtering

The idea of this nonlinear filter is to combine gray levels based on both the geometric closeness and photometric similarity that is in devour of adjacent values to distant values in both domain and range. Two weighting functions regarding spatial and radiometric information are designed to replace a pixel value with an average of similar and nearby pixel values in a (2N+1)×(2N+1) neighbourhood. In theory, any shape of weighting functions can be used but it is usually a Gaussian function in terms of the Euclidean distance between the arguments. More specifically, let (θx, θy) be the location of the pixel under consideration and

$$\Psi\theta_x,\theta_y = \{(\mu_x,\mu_y) : (\mu_x,\mu_y) \in [\theta_x - N, \theta_x + N] \times [\theta_y - N, \theta_y + N]\} \quad (6)$$

be the pixels in the neighbourhood of (θx, θy). The weighting functions for the spatial and radiometric components are defined respectively as

$$W^s\theta_x,\theta_y(\mu_x,\mu_y) = \exp[-|(\mu_x,\mu_y)-(\theta_x,\theta_y)|^2/2\sigma^2 S] \quad (7)$$

And

$$W^R\theta_x,\theta_y(\mu_x,\mu_y) = \exp[-|I(\mu_x,\mu_y)-I(\theta_x,\theta_y|^2/2\sigma^2 R] \quad (8)$$

Where I(·, ·) is the intensity value at the given position (·, ·). The ensemble weight in the bilateral filter is the product of (7) and (8)

$$W\theta_x,\theta_y\ (\mu_x, \mu_y) = W^S\theta_x,\theta_y\ (\mu_x, \mu_y) W^R\theta_x,\theta_y\ (\mu_x,\mu_y). \quad (9)$$

In practice, each pixel is filtered using normalized weights as

$$\tilde{I}(\theta_x,\theta_y) = \sum_{(\mu_x,\mu_y)\in\Psi} W\theta_x,\theta_y(\mu_x,\mu_y) I(\mu_x,\mu_y) / \sum_{(\mu_x,\mu_y)\in\Psi} W\theta_x,\theta_y(\mu_x,\mu_y) \quad (10)$$

Where $\tilde{I}$ (θ_x,θ_y) is the filtered image at location (θ_x, θ_y). It is noted that the contribution of the spatial weighting function WS decreases as the Euclidean distance between (θ_x,θ_y) and (μ_x,μ_y) increases and that of the radiometric weighting function WR decreases as the photometric difference increases. The parameters σS in (7) and σR in (8) are used to adjust the influence of WS and WR, respectively. They can be treated as rough thresholds for identifying pixels sufficiently close or similar to the pixel being filtered.

3. EXPERIMENTAL RESULTS

To evaluate and compare the proposed NLML technique with conventional LML and NL means scheme quantitatively, simulated MR magnitude data and MR data obtained from Yale MR Research Centre were used in this research. We generated MR magnitude data by adding Rician noise in noise-free images obtained from Brain Web.

3.1 Mean Square Error (MSE)

The MSE is the cumulative square error between the encoded and the original image defined by:

$$\mathrm{MSE} = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2 \qquad (12)$$

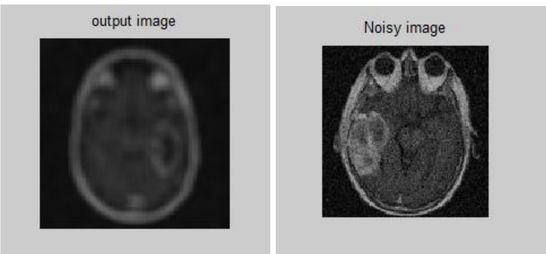
Where, f is the original image and g is the uncompressed image. The dimension of the images is m x n. Thus MSE should be as low as possible for effective compression.

3.2 Peak signal to Noise ratio (PSNR)

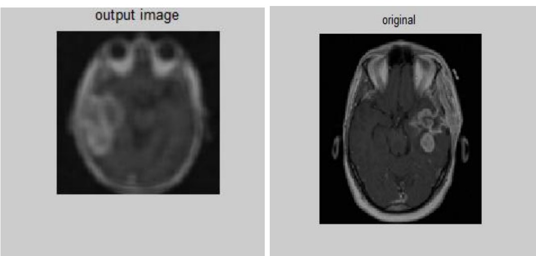
power of a signal and the power of distorting noise which affects the quality of its representation. It is defined by:

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{\mathrm{MAX}_f}{\sqrt{\mathrm{MSE}}}\right) \qquad (13)$$

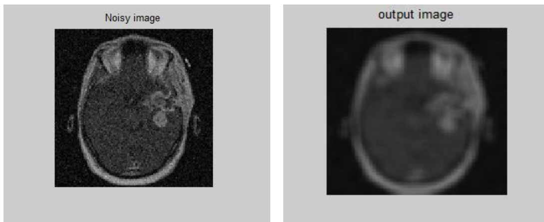
Where MAX_f is the maximum signal value that exists in our original “known to be good” image.



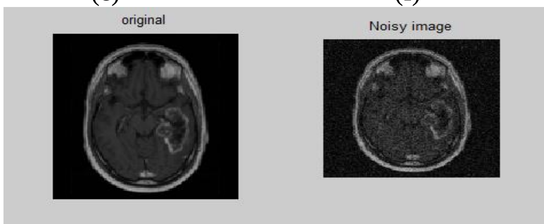
(a) (b)



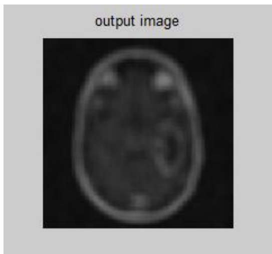
(c) (d)



(e) (f)

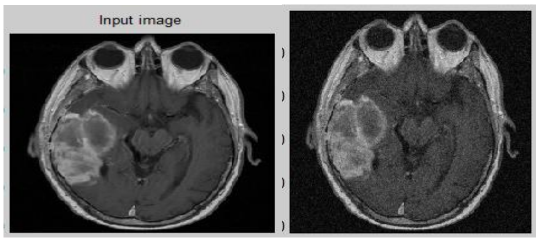


(g) (h)



(i)

Fig.1: Input, output and noisy MR images of NLML filter at different sigma values.



(a) (b)

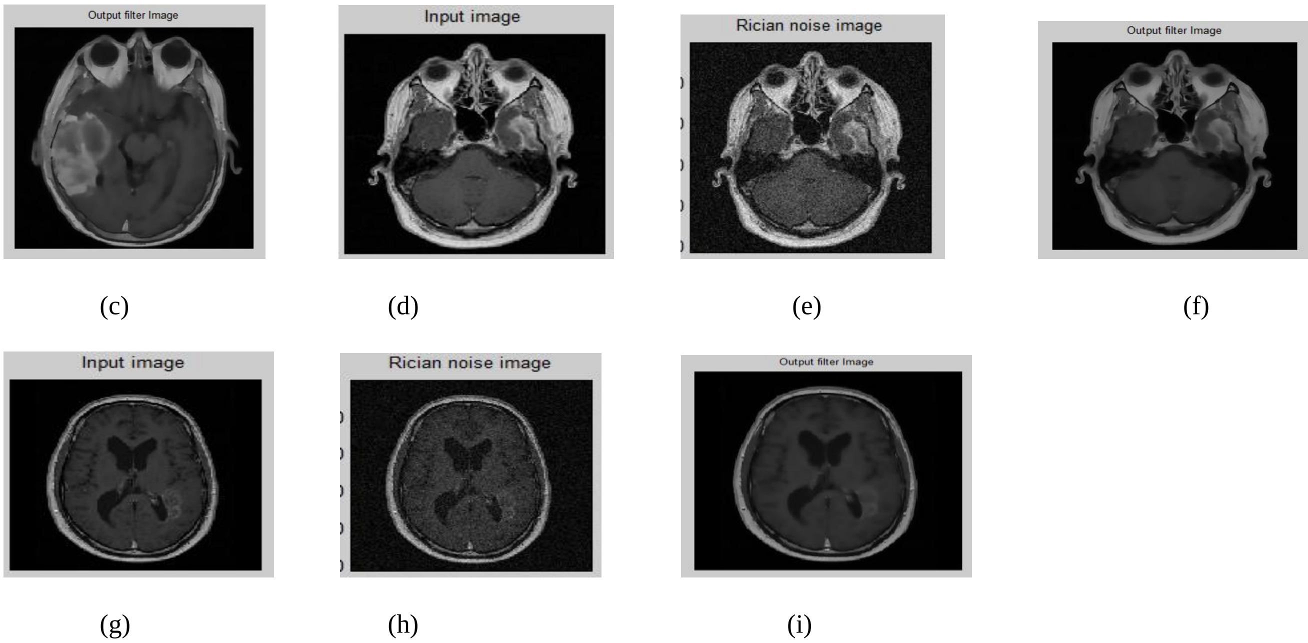


Fig.2: Input, output and noisy MR images of Bilateral filter at different sigma values.

Table 1: Comparison results of NLML & IBLF

Parameter	σ	Noisy Image	NLML	IBLF
PSNR SSIM	**5**	**29.8** **0.8242**	**28.01** **0.9031**	**34.44** **0.9499**
PSNR SSIM	**10**	**26.25** **0.7260**	**27.52** **0.8706**	**32.21** **0.9354**
PSNR SSIM	**15**	**23.73** **0.6471**	**27.26** **0.8342**	**30.22** **0.8998**
PSNR SSIM	**20**	**21.83** **0.5862**	**26.48** **0.7900**	**31.18** **0.8770**
PSNR SSIM	**25**	**20.28** **0.8007**	**25.82** **0.7481**	**30.47** **0.8553**

4. CONCLUSIONS

An iterative bilateral filter is method for denoising magnitude MR images. This iterative bilateral filter improves the denoising efficiency, extracts the edge features and fine structures in the image. For the comparative analysis, experiments were organized on both synthetic and real MR images, and for the synthetic images, mean SSIM and PSNR were used for the quantitative analysis. The iterative bilateral filter method is compared with the state-of-the-art methods like NLML. The visual and quantitative analysis shows that the iterative bilateral filter method outperforms the other methods.

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