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A Review on Rician Noise Removal Techniques for Magnetic Resonance Images

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Abstract: *This research work is targeted for image denoising and its improvement for Magnetic Resonance Imaging (MRI) images. The MRI is a special type of medical imaging technique, which shows clear structure of inner body parts like tissues and organs. Once the image gets corrupted with noise, its visual quality degraded and analysis of that noisy image becomes difficult. To improve the quality of noisy image, identification and reduction of noise is necessary. A wide variety of solutions for removal of noise from MR images have been proposed like Median filtering, Non Local Means filter, Maximum likelihood estimation and LMMSE (Minear Minimum Mean Square Error) Filtering. Most of the existing methods suffer with some drawbacks or limitations. This research proposes two novel denoising techniques for MRI images. Among available techniques, NLM filtering based techniques is very functional and possesses significant scope of improvement. The simulation results confirm the superiority of various methods as compared to existing denoising methods in removal of Gaussian as well as Rician noises.*

Keywords: MRI, Rician Noise, Gaussian Noise, Non Local means, PSNR, SSIM

I. INTRODUCTION

Image processing, in the field of medical science, is also known as Biomedical Image Processing or medical image processing. It includes the acquisition and processing of images of internal body structure like organs, tissues, etc [1]. During the acquisition, processing and communication, quality of image data of all kinds get affected by noise. The task of minimization of noise impact is called as denoising. Medical imaging technology has grown very fast become advance in last four decades. Various imaging techniques have been developed so far based on different principles and phenomenon.

The MRI modality of medical imaging is very advantageous of is due to higher resolution and clearer contrast difference between soft tissues which is very helpful in disease diagnosis and grading through medical image analysis and study. [2]

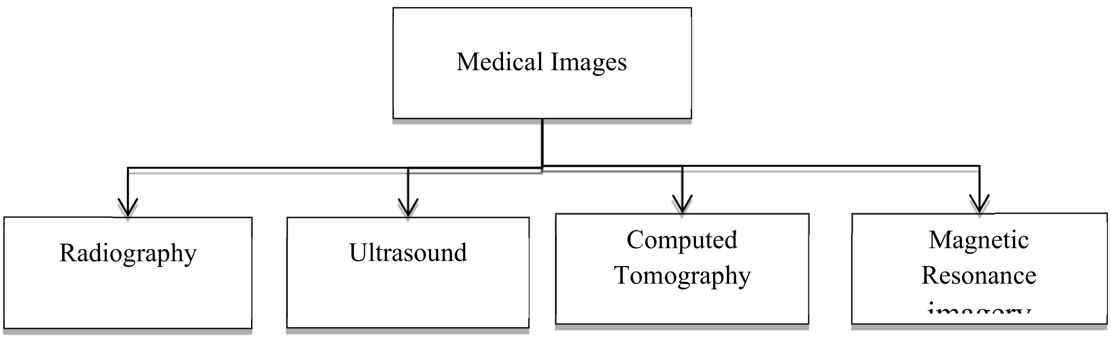

Figure 1. Typed of Medical Images

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Image denoising is a kind of image restoration and may be defined as the efforts for reduction/ removal of undesired distortions (noise). Generally acquired MR images are not perfect or distorted due to many causes, mainly imperfection in acquisition and processing [3]. In last two decades, several MRI denoising techniques have been proposed by different researchers to significantly suppress the noise while preserving the fine details [4]. Denoising techniques involve the detection and restoration the noisy pixels in entire image. Most of the MRI denoising technique functions through the analysis of neighbouring pixels called as neighbourhood [5]. The detailed explanation of most frequent noise corruptions of MRI images has been discussed in following section.

Noise Model for Medical Images:-

During acquisition or transmission, MRI images are mostly corrupted by noise. Noise is not only generated by receiving coil resistance, but inductive losses also include with it. The magnitude MRI images are best explained by a Gaussian distribution [6].

Magnitude Images:-

Magnitude images calculated using magnitudes of each pixel one by one from real and imaginary images. The probability distribution for measured pixel intensity can be shown as

$$p_M(M) = \frac{M}{\sigma^2} e^{-\frac{A^2+M^2}{2\sigma^2}} I_0\left(\frac{A.M}{\sigma^2}\right) \quad (1)$$

Where A is represent original pixel intensity and M as measured pixel intensity.
I_0 = Modified zeroth order Bessel function of the first kind and
σ= standard deviation of the Gaussian noise
It is observed that the distribution of noise is expressed as :

$$\frac{A}{\sigma} = \begin{cases} \frac{A}{\sigma} = 0 & \text{Rayleigh distribution} \\ 1 \le \frac{A}{\sigma} \le 3 & \text{Rician distribution} \\ \frac{A}{\sigma} \ge 3 & \text{Gaussian distribution} \end{cases} \quad (2)$$

II. LITERATURE OF MRI DENOISING METHODS

A variety of efforts have been done using diverse approaches for reduction of noise impact on image quality which is commonly addressed as de-noising techniques. Noise removal process can be categorized in two ways, noise removal during image acquisition and noise removal after acquisition. The removal of noise during acquisition leads to the increase in acquisition time. MR imaging is a time consuming modality of medical imaging and further increase in acquisition time may lead to discomfort for patient [7]. Hence, noise removal after image acquisition is preferred. The post-acquisition denoising techniques may be categorized in three sections; transform domain, statistical domain and filtering domain [10]. Some standard methods are basically based on the assumption that noise is spatially uniform noise distribution. Another nonlinear filter is Non local means (NLM) filter which is based on providing different weights to neighbours and taking average of those pixels.

2.1 Linear Minimum Mean Square Error

Linear Minimum Mean Square Error (LMMSE) based techniques used the local-variance and local-mean for Rician noise removal [8]. It uses local neighbourhood for restoration of denoised value of targeted pixel. Golshan and Hasanzadeh in, have used non local neighbourhood with LMMSE estimation method for 3D MRI image denoising. This method has been modified in future by updating of control parameter with noise level [13]. It uses similarity measurement for selection of the other required parameters automatically.

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2.2 Non Local Means Filter:-

NLM filter [16] were introduced as improvement in Yaroslavsky filter, which work on the principle of averaging similar pixels based on their intensity distance. NLM filter uses region comparison instead of pixel comparison. It is based on the similarity between targeted pixels and its neighbourhoods and the similarity is measured by Euclidean distance between pixels. Based on that similarity, different weights are provided to the neighbours. Then weighted averaging of neighbouring pixels is calculated to get denoised value. Various NLM based filtering techniques have been suggested thereafter for further improvements

The weighted average of NLM filter is based on the formula

$$NLM\left(Y(p)\right) = \sum_{\forall q \in Y} W(p,q)\, Y(q) \qquad (2)$$

Where

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

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

Z(p) = normalizing constant,

h = exponential decay control parameter

d = Gaussian weighted Euclidian distance which shows the order of similarity.

To reduce the number of voxels used to calculate the weighted average, Pierrick et al [17] suggested fast NLM filter. They have considered the voxels having higher similarity weights and neglects the other voxels possessing smaller similarity. The similarity measurement is calculated by mean and gradient of both the patches. The neighborhoods with close mean and close gradient are only considered.

2.3 Advanced Non Local Methods:-

G. Chen et al. [11] proposed Collaborative Non-local Means (CNLM) filtering algorithm. Rather than working on a single image, This method uses scanned multiple images (coordinating images) to denoised one target image. This method is based on the concept of repeating structural pattern. Multiple images may be acquired from different subjects and these images will help to denoised target image. Block-wise NLM filtering is performed on all images to match similar blocks with target image. The final denoised value will be a weighted average of all coordinating images restored by NLM filter. This concept increases the number of similar patterns and in turn improves the denoising performance.

III. COMPARATIVE ANALYSIS

Quantitative analysis involves numerical results, statistics and value comparison. The numerical parameters considered here are; Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), or Structural Similarity Index Measure (SSIM) [14]. The analysis of existing state of art methods have be performed on the basis of quantitative measure. The experiment outcome has been presented on T-1 weighted MRI image [15] for different level of Gaussian and Rician noise.

PSNR defines the performance of algorithm and it represents mathematically as

$$PSNR = 10 \log\left[\frac{255^2}{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}\left(I(i,j) - \hat{I}(i,j)\right)^2}\right] \qquad (5)$$

Where M xN is size of the image $I(i,j)$ represents original image and $\hat{I}(i,j)$ represents restored image.

Another quality measures is Structural similarity index matrix (SSIM), which specify the human visual system.

$$SSIM(x,y) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_{xy} + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)} \qquad (7)$$

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The parameters $\mu_x$and μ_y represrnt mean value of images x and y. σ_x and σ_y are standared deviation of images x and y. σ_{xy} represents covariance of x and y. Constant C_1 and C_2 are $C_1 = (K_1L)^2$ and $C_2 = (K_2L)^2$, where L is dynamic range and $K_1 = 0.01$, $K_2 = 0.03$. For 8 bit images, the value of L is 255 for 8 bit gray images.

Figure 2 showing the Simulated T1, PD and T2 phantom images. The results are compared for different denoising algorithms for different noise densities experimented on brainweb T1 weighted phantom image. The Table 1 showing the quantitative analysis based on PSNR of different denoising techniques like Fast NLM, LMMSE and morphological component analysis MCA (Morphological Component Analysis) Filtering. The Table 2 showing the SSIM analysis of for Fast NLM, LMMSE and MCA Filtering.

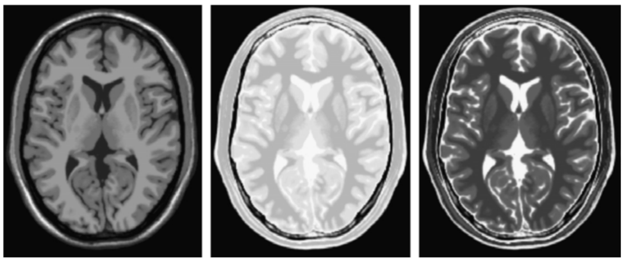

Figure 2. Simulated MR images (T1, PD and T2) from the Brainweb phantom [64]

TABLE I: Peak Signal to Noise Ratio (PSNR) in dB

Sr. no.	**Technique**	**Noise Density (σ)**			
		3	**5**	**7**	**11**
	Noisy	36.74	31.87	30.80	28.58
	Fast NLM [17]	37.70	35.18	32.15	29.52
	LMMSE [8]	37.63	33.26	31.30	28.90
	MCA Filtering [12]	38.39	35.88	33.57	30.57

TABLE III: Structural similarity index matrix (SSIM)

Sr. no.	**Technique**	**Noise Density (σ)**			
		3	**5**	**7**	**11**
	Noisy	0.9000	0.8834	0.8380	0.7659
	Fast NLM [17]	0.9295	0.9316	0.9057	0.8035
	LMMSE [8]	0.9271	0.9227	0.8910	0.8005
	MCA Filtering [12]	0.9396	0.9423	0.9195	0.8074

IV. CONCLUSION

The improvement of the denoising quality of standard NLM filter by selecting the parameters properly but suffers with high computational complexity. Fast NLM [17] reduce the burden of computation. In optimized block wise NLM [18] the smoothing parameter *h* is tuned automatically and preserve the edges and fine details. The MCA Filtering [12] MCA break down an image into its various morphological components, it makes it easy to combine several techniques. The NLML [10] offers the clear boundaries on the cost of high probability of under or over smoothening. Few methods suffer with blurring effect, few of them are good for Gaussian noise, but not suitable for Rician noise. Some methods fails to preserve edges and fine details. The research objectives have been casted on the basis research gaps identified in literature survey. The denoising techniques must effectively remove the noise content and also preserve the edges and fine details of images.

REFERENCES

[1]. RakaKundu, AmlanChakrabarti, “De-Noising Image Filters for Bio-Medical Image Processing”, CSI Communications Magazine 01/2014.

[2]. SigurdAngenent, Eric Pichon, Allen Tannenbaum, “Mathematical Methods In Medical Image Processing”, Bulletin (New Series) Of The American Mathematical Society, 2005.

[3]. W.C. Roentgen, Uebereineneue Art von Strahlen, Annalen der Physik 64 (1898), 1–37.

[4]. http://www.ctscaninfo.com/mrivsctscan.html

[5]. HákonGudbjartsson and Samuel Patz, “The Rician Distribution of Noisy MRI Data”, MagnReson Med. 1995 December; 34(6): 910–914.

[6]. Henkelman RM. “Measurement of signal intensities in the presence of noise in MR images”, Med Phys, 1985; 12:232–233. [PubMed: 4000083]Erratum in 13, 544 (1986).

[7]. Rice SO. Mathematical analysis of random noise. Bell System Tech J 1944; 23:282.Reprinted by N.Wax, Selected Papers on Noise and Stochastic Process, Dover Publication, 1954, QA273W3.

[8]. S. Aja-Fernandez, C. Alberola-Lopez, C. F. Westin, “Noise and signal estimation in magnitude MRI and Rician distributed images: a LMMSE approach”, IEEE Transaction on Image Processing. 17, 2008, pp. 1383.

[9]. Abhishek Sharma, VijayshriChaurasia, ‘ MRI Denoising Using Advanced NLM Filtering With Non-Sub Sampled Shearlet Transforms ', International Journal of Signal, Image and Video Processing (SIVP), 15, 2021, 1331–1339.

[10]. Mohana,∗, V. Krishnavenib, YanhuiGuoca, “A survey on the magnetic resonance image denoising methods”, Biomedical Signal Processing and Control 9 (2014) 56– 69.

[11]. G. Chen, P. Zhang, Y. Wu, D. Shen, P. Yap, “Denoising magnetic resonance images using collaborative non-local means”, Neurocomputing, 177, 2016, pp. 215-227.

[12]. Yanqiu Zeng, Baocan Zhang,1 Wei Zhao ,Shixiao Xiao,1 Guokai Zhang ,Haiping Ren ,3 Wenbing Zhao,4 Yonghong Peng , Yutian Xiao, Yiwen Lu,Yongshuo Zong, and Yimin Ding, “Magnetic Resonance Image Denoising Algorithm Based on Cartoon, Texture, and Residual Parts”, Computational and Mathematical Methods in Medicine, 2020.

[13]. H.M. Golshan, R.P.R. Hasanzedeh, S.C. Yousefzadeh, An MRI denoising method using data redundancy and local SNR estimation, Magn. Reson. Imaging 31(2013) 1206–1217.

[14]. S. Aja-Fernandez, A. Tristan-Vega, C. Alberola-Lopez, Noise estimation in sin-gle and multiple coil MR data based on statistical models, Magn. Reson.Imaging 27 (2009) 1397–1409.

[15]. https://brainweb.bic.mni.mcgill.ca/brainweb

[16]. Jose V. Manjon, Jose Carbonell-Caballero, Juan J. Lull, Gracian Garcıa-Martıa, Luıs Mart-Bonmat, Montserrat Robles, “MRI denoising using Non-Local Means”, Medical Image Analysis 12 (2008) 514–523.

[17]. Pierrick Coupe, Pierre Yger, and Christian Barillot, “Fast Non Local Means Denoising for 3D MR Images”, R. Larsen, M. Nielsen, and J. Sporring (Eds.): MICCAI 2006, LNCS 4191, pp. 33–40, 2006.

[18]. Pierrick Coupe, Pierre Yger, Sylvain Prima, Pierre Hellier, Charles Kervrann, and Christian Barillot, “An Optimized Blockwise Nonlocal Means Denoising Filter for 3-D Magnetic Resonance Images”, IEEE Transactions On Medical Imaging, VOL. 27, NO. 4, APRIL 2008