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De-Noising Functional Magnetic Resonance Imaging (fMRI) Data Using an Exponential Gradient Filter

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Abstract: Unlike Gaussian noise, Rician noise filtering is more challenging, since this type of noise exists in Functional Magnetic Resonance Imaging (fMRI) data which makes the analysis of fMRI data very difficult for experimental and clinical purposes. To cope with the situation, normally (smoothing) de-noising is done before the analysis of the data using conventional methods like Gaussian filtering as done in Statistical Parametric Mapping (SPM). However results of conventional filtering are not satisfactory. In this work a specially designed filter for fMRI data de-noising is presented. Weights of this filter are calculated by taking the difference of spatial neighboring pixels in each direction of a predefined window. The proposed filter outperforms when applied to synthetic and actual fMRI data. Results of the proposed and state of the art filters are compared using correlation, PSNR and Mean Square Error (MSE). Furthermore, proposed filter can be used not only for fMRI de-noising but also on other problems where Rician noise exists.

Key words: fMRI · Image de-noising · Rician noise · Signal processing · Image filtering

INTRODUCTION

The most well known and latest technique for detecting the functionality of brain is Functional Magnetic Resonance Imaging [1]. It is a non-invasive technique in which Blood-Oxygen-Level-Dependent (BOLD) signal is acquired by the fMRI scanner during physical or mental activity [2]. For observing BOLD signal changes, a number of images are acquired, which are then analyzed and the result is expressed on functional activation map of the brain [1]. Changes in BOLD signal due to activity are very low, thus fMRI data suffers from a very low SNR [3]. Therefore, fMRI data need to be preprocessed (de-noised) before classification. Furthermore, MR data is corrupted by Rician noise [4], which is the most difficult noise from filtering point of view.

Nuclear Magnetic Resonance (NMR) signal is measured using a quadrature detector consisting of real and imaginary parts. Noise in each signal component is assumed to be Gaussian distributed with equal variance. MRI scanner normally gives the magnitude of the complex data as its output. Due to the nonlinear transformation of Gaussian noise in the complex space, the resultant noise is Rician distributed. Due to this Rician noise NMR signal becomes biased, which is normally an overestimation as compared to its true value [5] along with fluctuations in the signal which reduces the image contrast. Rician noise is a signal dependent noise, rather than a simple additive noise which is relatively easy to filter out. The areas of the image having low intensity are considered having noise with Rayleigh distribution while higher intensity regions are considered Gaussian distribution corrupted. Overall, the noise tendency is considered to be Rician distributed. Rician noise degrade images in both, quantitative and qualitative measures thus making it difficult to perform analysis, interpretation and feature detection. Therefore, it is highly desirable to develop such filters which are specifically suitable for Rician noise removal [6].

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Conventional method used for fMRI data de-noising is Gaussian filtering [7]. In fMRI data there are functionally active regions of different shapes, thus Gaussian kernel defined for one region is not generally suitable for other regions thus causing blur in the images [8]. Wavelet based smoothing is used for the avoidance of blurring effect [9]. In literature [10-12] have proposed other techniques for filtering the fMRI data. Anisotropic averaging is another technique proposed by [13] which is basically inspired from the work of anisotropic diffusion [14] and is further refined by [3] in which a metric is formed by looking for highly activated voxels from which reference time courses are constructed which are used for filtering purposes. Some adaptive temporal filtering schemes have also been used on fMRI data like Wiener filtering [15], FIR filtering [16] and spectral subtraction [17]. Once the data is de-noised, then it is ready to be analyzed by different classification techniques including PCA, ICA and artificial neural networks which is not in the scope of this study and hence will not be discussed.

Work done in this paper is more relevant to [18] in which non local mean de-noising of MRI data is being done using un-biased non-local mean (UNLM). In our proposed work we have extracted gradient based weights from the image which are used for filtering the mean square image. The result is then unbiased using the estimated Rician noise variance.

Remaining article is represented as follows. Section 2 explains the background theory of NLM filter and noise variance estimation. Details of the suggested method are explained in section 3. Section 4 and 5 elaborates data and simulation results respectively. Concluding remarks are presented in section 6.

Background and Theory

Non Local Mean Filter: Non Local Mean (NLM) filter was first suggested by [19] which was then further refined and implemented on MR images by [18]. Details of NLM filter are as under.

For a noisy image I, filtered value f of pixel p is calculated as given by equation (1) [18].

$$f(p) = \sum_{r \in I} w(p,r).I(r) \qquad (1)$$

where p is the pixel being filtered, r represents each pixel in the image and $w(p,r)$ are the similarity weights being defined by equation (2)

$$w(p,r) = \frac{\exp-\left[\ d(p,r)/h^2\ \right]}{\sum_{\forall r} \exp-\left[\ d(p,r)/h^2\ \right]} \qquad (2)$$

where h is the decaying or smoothing factor and $d(.)$ is the Gaussian weighted Euclidian distance of all the pixels in each neighborhood given by equation (3)

$$d(p,r) = g\left\| I(N_p) - I(N_r) \right\|_R^2 \qquad (3)$$

here g is the normalized Gaussian weighted function and N_p,N_r are user defined windows [20].

Output of equation (1) is biased case of MR images so [18] (Manjo´n *et al.* 2008) have used equation (4) for reducing the bias of the noisy MR data.

$$Unbiased(f) = \sqrt{f^2 - 2\sigma_n^2} \qquad (4)$$

where σ_n^2 is the estimated Rician noise variance, while f represents a squared image.

Noise Variance Estimation: In the above technique noise variance is required to be estimated as well. Accuracy of signal estimation from noisy magnitude image data is dependent on the estimation of noise variance.

Research on a number of methods for Rician noise estimation exists in the literature. Noise variance σ_n^2 can be estimated using a single image or using multiple images.

Rician Noise Variance from Single Magnitude Image: Rician noise estimation technique from a single image is based on the assumption that there is a sufficient background area where there is no signal present in the image thus following Rayleigh distribution. Therefore noise variance estimation [21] can be written as

$$\hat{\sigma}_n^2 = \frac{1}{2}\frac{1}{N}\sum_{k=1}^{N} M_k^2 \qquad (5)$$

Here N represents the number of Pixels in the window under consideration.

There is another algorithm which uses the histogram of the noisy image. The approach assumes that signal intensity in the background of the image is zero. A sharp peak at zero histogram is the result of such an image having no noise. However, if noise is present in the image, then the resulting histogram is shifted to value nearly equal to the noise variance σ_n^2 value [21].

$$\hat{\sigma}_n^2 = \frac{1}{2}\operatorname{mod}e\left[\hat{\mu}_{2ij}\right] \qquad (6)$$

In equation (6) $\hat{\sigma}_n^2$ is the second moment of the magnitude MR image.

Another approach for noise estimation is also used in the literature which is based on the 2nd and 4th order moment of Rician distributed data [21].

$$\hat{\sigma}_n^2 = \frac{1}{2}\left(E[M^2] - \left(2E[M^2] - E[M^4]\right)^{0.25} \right) \tag{7}$$

Where M is the magnitude noisy image. Rician noise variance estimator based on magnitude image variance is also proposed by [21]. Here again it is assumed that the signal strength of background pixels is zero.

$$\hat{\sigma}_n^2 = \sigma_M^2 \left(2 - \pi/2\right)^{-1} \tag{8}$$

Rician Noise Variance Estimation Based on Multiple Images: Rician noise estimation based on single image methods suffers few disadvantages like large homogeneous regions with no signal. In some cases this requirement is not met thus making the estimation process prone to errors. To cover this issue, methods have been developed which uses two versions of the same image [4].

$$\hat{\sigma}_n^2 = E[M_s^2] - E[M_a^2] \tag{9}$$

Where M_s and M_q are single and averaged magnitude images.

Proposed Technique

Estimation of Pixel Values: Normally variation in the intensity of adjacent pixels is very small. Thus, there should be no abrupt changes in the neighboring pixels. However, if the difference is large then it means that pixel under consideration is corrupted with noise. Keeping in view this fact, exponential gradient weights are calculated. It should further be noted that the approach of [22] for signal estimation is based on the weights which are estimated from the time series of all images. However, here we estimate weights using only a single image.

Let M_1 is the first image being processed by the suggested technique and $l_{i \in 1,9}$ is a 3x3 window of M_1. L_5 is the pixel which is under consideration.

$$L_5 = \begin{bmatrix} l_1 & l_2 & l_3 \\ l_4 & l_5 & l_6 \\ l_7 & l_8 & l_9 \end{bmatrix} \tag{10}$$

Then

$$w_i = \exp\left[-\frac{|\nabla_i|}{0.25|\nabla|_{\max}} \right] i = 1,2,3.....9 \tag{11}$$

Where

$$\nabla_i = (l_i) - (l_5)\; i = 1,2,3.....9 \tag{12}$$

Processed central pixel of the 3x3 window is calculated as

$$f_5 = \frac{\sum_{i \in 1,9} w_i \,.\, l_i'}{\sum_{i \in 1,9} w_i} \quad i = 1,2,3.....9 \tag{13}$$

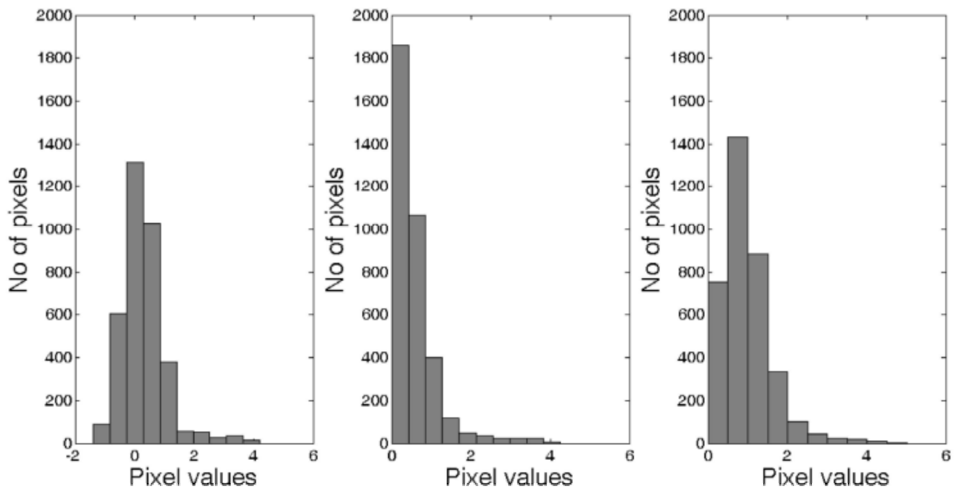
Where l_i' is the output of the mean filter having an input L_5. In a similar way all pixels of the image M_1 are processed and filtered out thus making complete image$F$. However, this image is still biased and can be made cleaned using equation (14).

$$Unbiased(F) = \sqrt{F^2 - 2\sigma_n^2} \tag{14}$$

Where σ_n^2 is the Rician noise variance and is necessary for complete filtering process. Steps for finding out σ_n^2 are depicted in section 3.2. Thus a single fMRI image is de-noised. To clean out all images, the procedure needs to be repeated for all images.

Noise Variance Estimation: Accurate noise variance estimation is the key requirement of de-noising in fMRI data. Noise estimation techniques discussed earlier are not suitable for fMRI data because there is no zero signal (background) in this case. Authors of [22] have suggested a histogram based method for variance estimation. In this proposed scheme we are estimating Rician noise variance using equation (15), which uses histogram method of noise estimation. Estimated variance found out by the proposed method is biased, as can be seen in Figure 1 which shows histogram of a simulated fMRI image with no noise i.e. sigma =0,with noise sigma=0.1 and sigma=0.6 respectively. By taking a large number of observations using equation (15) it became evident that noise estimation is biased by almost 33 percent. To remove the bias, equation (16) is used which is proposed by [22].

$$\hat{\sigma} = Mode.(M_1) \tag{15}$$



(a) Sigma=0 (b) Sigma=0.1 (c) Sigma=0.6

Fig. 1: Histogram of the image with different sigma (Noise STD) values

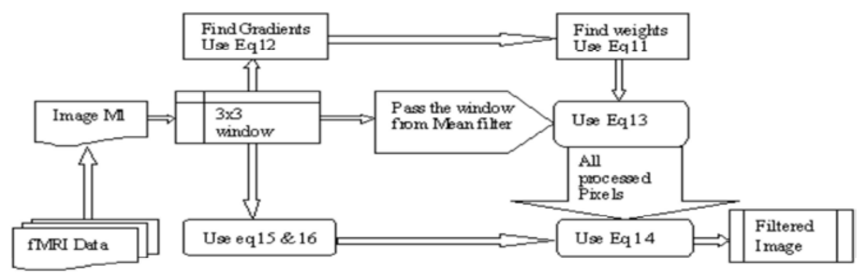


Fig. 2: Schematic Diagram of the suggested Filter

$$\hat{\sigma}_n = 0.67\hat{\sigma} \tag{16}$$

A schematic diagram of the suggested method is shown in Figure 2.

To further clarify the proposed scheme a step by step procedure is mentioned as under.

Step 1: Select a 3x3 window in the first fMRI image to be de-noised.

Step 2: Using equation (11) find gradient based weights of the filter from 3x3 window.

Step 3: Using Mean filter process the 3x3 window.

Step 4: Filter the center pixel of the 3x3 window using equation (13).

Step 5: Repeat the above steps until all pixels are de-noised.

Step 6: Estimate Rician noise using equation (15) and equation (16).

Step 7: Use equation (14) to find un-biased filtered image.

Step 8: Use the above steps iteratively to de-noise all images.

Data: Since actual fMRI data is complex and no ground truth is available for it, therefore it is a common practice to use synthetic fMRI data for testing the performance of any proposed algorithm. The results obtained from simulated data are assumed to be equally valid for actual fMRI data. Thus accurate and near to actual fMRI data is necessary for research purposes. Different sources on web are available where one can find synthetic fMRI data for research purposes. [Source: simulated fMRI data (http://mouldy.bic.mni.mcgill.ca/brainweb/)

Synthetic fMRI data: In this work synthetic fMRI data is acquired from Machine learning and Processing Lab University of Maryland Baltimore county USA [23].

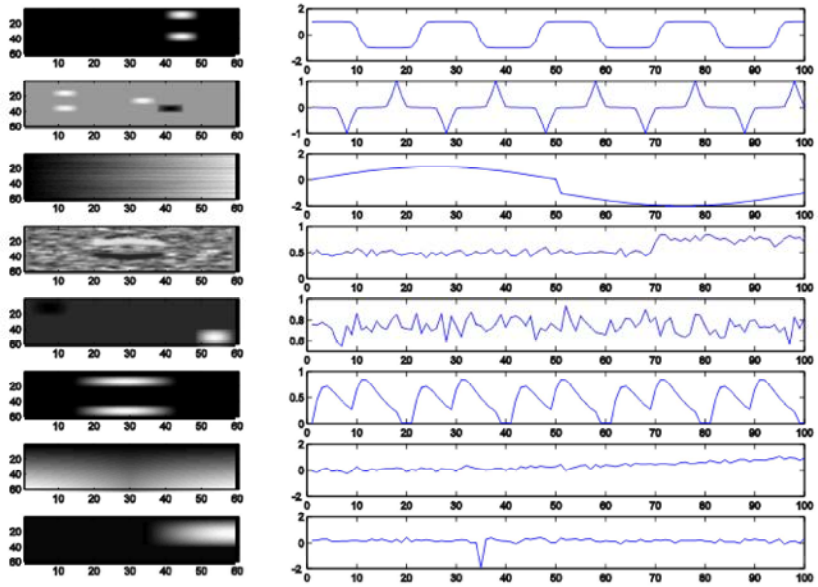


Fig. 3: Sources and Time courses

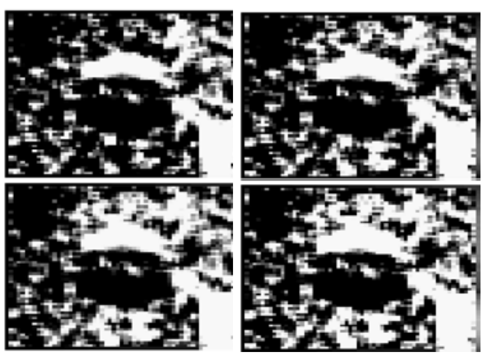


Fig. 4: Four sample images of simulated fMRI.

This data comprises of 100 images each of 60x60. The data is formed by a set of sources shown in Figure (3) [23]. Which consists of one Gaussian source, five super-Gaussian and two sub-Gaussian sources. Eight time courses are also shown which consists of task related transiently task related and artifact related. Each source image dimension is 60x60 with 100 time points. Thus there exists 100 images each of 60x60. Data available for processing is formed by the multiplication of time series matrix with the Image data. Since, in this case time course matrix consists of 100 entries, thus a mixture of 100 scans. Figure 4 shows only 4 images of the observed fMRI data [23]. Synthetic data thus formed is not noisy, However, it is a mixture of the actual images and time courses. It is a challenging job to separate these sources and time courses. To make this data noisy, equation (17) is used for different noise levels.

$$M = \sqrt{\left[\left(\left(\hat{\sigma}_n * randn\right) + \left(F\right)\right)^2 + \left(\hat{\sigma}_n * randn\right)^2\right]} \qquad (17)$$

F is the noise free synthetic fMRI image, *randn* is the zero mean unit variance Gaussian noise and σ_n is the noise standard deviation.

Real fMRI Data: Actual fMRI data can be acquired from different sources. Data used in this work is acquired from the data repository of carneige mellon university USA. Details of which can be found at http//www.cs. cmu. edu/afs/cs. cmu.edu/project/theo-81/.

RESULTS AND DISCUSSION

Equation (17) is used to corrupt synthetic fMRI data with known noise levels. One exemplary non noisy and noisy image is shown in Figure 5 (a) and (b) respectively. Noisy synthetic fMRI image is smoothed out using the suggested and state of the art methods. Figure 5 (c) (d) (e) (f) (g) (h) shows the visual effects of de-noised image by Mean, Median, Wiener, NLM and Anisotropic filters and proposed filter. Visual performance of the suggested filter is good as compared to state of the art filters. For the case of synthetic data we have ground truth or non noisy data available, therefore, results of the suggested and state of the art techniques are compared using correlation SSIM, PSNR and RMSE etc. Figure 6 and Figure 7 shows the performance of the suggested and state of the art filters in

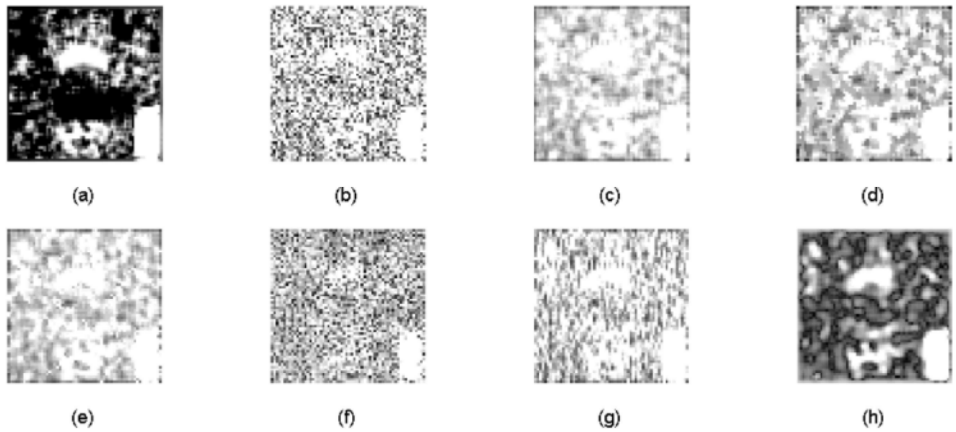


Fig. 5 : (a) Simulated fMRI Image (b) fMRI noisy image with noise standard deviation=0.6 (c) Processed fMRI Image by Mean filter (d) by Median filter (e) by Wiener filter (f) by NLM filter (g) by Anisotropic filter (h) by Proposed filter

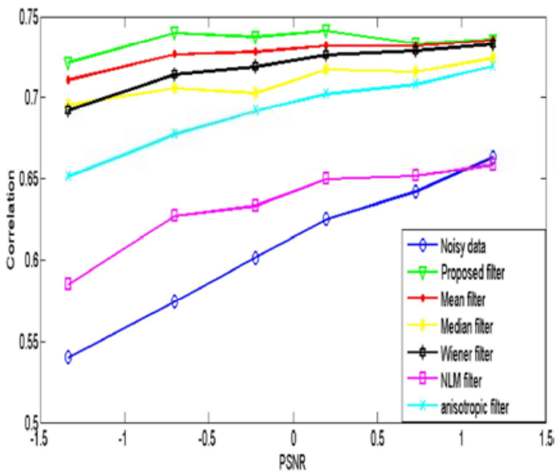


Fig. 6: Correlation VS PSNR

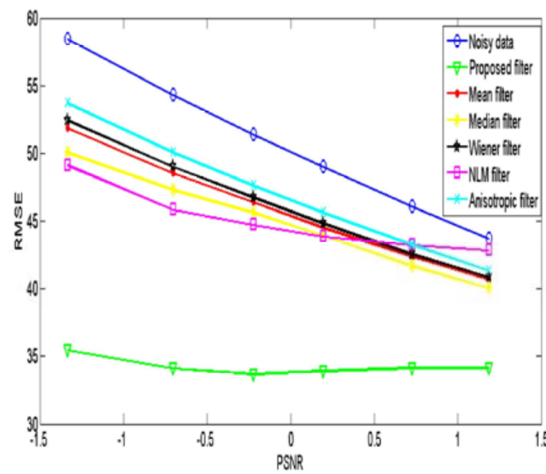


Fig. 8 RMSE VS PSNR

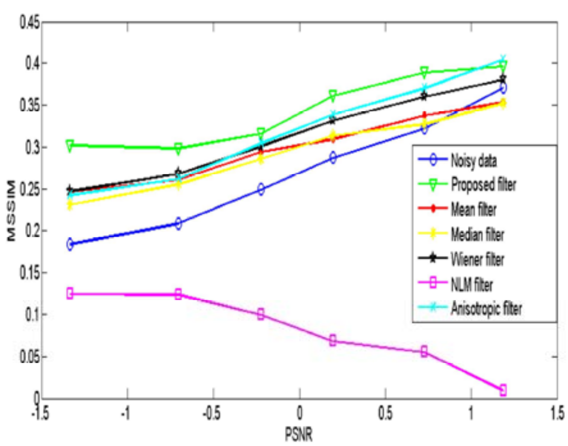


Fig. 7: MSSIM VS PSNR

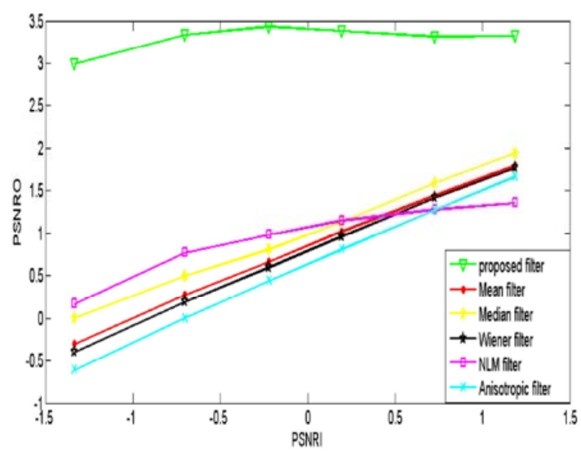


Fig. 9: PSNRO VS PSNRI

Table 1: Performance comparison (unprocessed noisy image PSNR is -1db)

Filter/parameter	Correlation	MSSIM	PSNRO	RMSE
Mean	0.72	0.25	0.0	50
Median	0.70	0.24	0.56	48
Wiener	0.71	0.26	0.10	51
NLM	0.61	0.12	0.50	47
Anisotropic	0.67	0.25	-0.30	52
Proposed spatial filter	0.73	0.31	3.2	35
Un-processed noisy image	0.56	0.21	-1	57

terms of correlation and MSSIM. Suggested filter is slightly good keeping in view the correlation and MSSIM results.

The horizontal axis in Figure 6 shows PSNR which is a peak signal to noise ratio of actual and noisy image with different noise levels. In Figure 6 where correlation is used as a quality measure vertical axis shows correlation values for actual and noisy image, actual and de-noised image (of course by proposed and other techniques), Where it can be seen that for a specific PSNR value i.e. -0.5 db correlation of actual and noisy image is 0.57 while that of de-noised image by proposed filter is 0.74 and correlation of other filters is less than that. Same way of reading can be adopted for other figures. It should be noted that MSSIM, PSNRO and RMSE are qualitative measure for processed images in this case.

The performance results of suggested and state of the art techniques are compared in terms of PSNR and RMSE and are shown in Figure 8 and Figure 9 respectively. It is evident that proposed technique out performs keeping in view PSNR and RMSE.

The results of the suggested and state of the art filters are also shown in tabular form in Table 1. Figure 10 shows noisy and de-noised actual fMRI slice. It is apparent that sudden changes have been smoothed out in the resultant slice.

CONCLUSION

In this work we proposed an exponential gradient based Rician noise removal filter specifically suitable for fMRI data. Filter weights are extracted from spatial images exploiting the structural similarity of the neighboring pixels. Filtered image was further refined by subtracting bias from the image. The performance of the proposed filter was compared to conventional filters. Experimental results show that suggested technique is slightly good in terms of SSIM and correlation while reasonably good in terms of PSNR and RMSE from the conventional filters. The proposed technique can be tailored for other application having Rician noise.

Figure. 5 (a) Simulated fMRI Image (b) fMRI noisy image with noise standard deviation=0.6 (c) Processed fMRI Image by Mean filter (d) by Median filter (e) by Wiener filter (f) by NLM filter (g) by Anisotropic filter (h) by Proposed filter

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REFERENCES

1. Orrison, W.W., et al., 1995. Functional Brain Imaging. St. Louis, MO: Mosby-Year Book.
2. Ogawa, S., et al., 1992. Intrinsic signal changes accompanying sensory stimulation: functional brain mapping with magnetic resonance imaging, Proc. National Academy of Science US, 89: 5951-5955.
3. Monir, S.M. and M.Y. Siyal, 2009. De-noising functional magnetic resonance imaging time-series using anisotropic spatial averaging, Biomedical Signal Processing and Control, 4: 16-25.
4. Karpagam, S. and S. Gowri, 2013. Development of an Optimized Glioma Prediction Technique Using Genetic Algorithm Based Neural Network. Middle-East Journal of Scientific Research, 16(2): 210-220.
5. Gudbjartsson, H. and S. Patz, 1995. The Rician distribution of noisy MRI data, Magnetic Resonance in Medicine, 34: 910-914.
6. Manikandan, R., G.S. Monolisa and K. Saranya, 2013. A Cluster Based Segmentation of Magnetic Resonance Images for Brain Tumor Detection. Middle-East Journal of Scientific Research, 14(5): 669-672.
7. Huettel, S.A., A.W. Song and G. McCarthy, 2004. Functional Magnetic Resonance Imaging, Sinauer Associates Inc.
8. Friman, O., M. Borga, P. Lundberg and H. Knutsson, 2002. Detection of neural activity in fMRI using maximum correlation modeling, NeuroImage, 15: 386-395.
9. Wink, A.M., J.B. Roerdink and T.M. De-noising, 2004. Functional MR Images: a comparison of wavelet de-noising and Gaussian smoothing, IEEE Transactions on Medical Imaging, 23: 374-387.

10. Goutte, C., et al., 1999. On clustering fMRI time series, NeuroImage, 9: 298-310.
11. Ardekani, B.A. and I. Kanno, 1998. Statistical methods for detecting activated regions in functional MRI of the brain. Magnetic Resonance Imaging, 16: 1217-1225.
12. Baudewig, J., P. Dechent, K.D. Merboldt and J. Frahm, 2003. Thresh holding in correlation analyses of magnetic resonance functional neuro-imaging, Magnetic Resonance Imaging, 21: 1121-1130.
13. Sole, A.F., L.C. Ngan, G. Sapiro, X.P. Hu and A. Lo´ pez, 2001. An-isotropic 2-D and 3-D averaging of fMRI signals, IEEE Transaction on Medical Imaging, 20: 86-93.
14. Perona, P. and J. Malik, 1990. Scale-space and edge detection using anisotropic diffusion, IEEE Transaction Pattern Analysis and Matching Intelligence, 12: 629-639.
15. LaConte, S.M., N. Shing-Chung and H. Xiaoping, 2000. Wavelet transform based wiener filtering of event related fMRI data, Magnetic Resonance in Medicine, 44: 746-757.
16. Goutte, C., F.A. Nielsen and K.H. Hansen, 2000. Modeling the hemodynamic response in fMRI using smooth FIR filters, IEEE Transactions on Medical Imaging, 9: 1188-1201.
17. Kadah, Y.M., 2004. Adaptive de-noising of event-related functional magnetic resonance imaging data using spectral subtraction, IEEE Transactions on Biomedical Engineering, 51: 1944-1953.
18. Manjòn, J.V. et al., 2008. MRI de-noising using non-local means, Med Image Anal, 4: 514- 523.
19. Buades, A., B. Coll and J.M. Morel, 2005. A review of image de-noising algorithms, with a new one. Modeling and Simulation, 4: 490-530.
20. Yifei, Lou, et al., 2010. Image Recovery via Nonlocal Operators, Journal of Scientific Computing, 42: 185-197.
21. Aja-Fernández, S., C. Alberola-López and C.F. Westin, 2008. Noise and signal estimation in magnitude MRI and Rician distributed images: A LMMSE approach, IEEE Transactions on Image Processing, 17: 1383- 1398.
22. Amir, A.K., I.M. Qureshi and J.A. Shaha, 2012. Temporal Correlation based spatial filtering of Rician Noise for Functional MRI, Chinese Physics Letters, 29(1), DOI:10.1088/0256-307X/29/1/018701,
23. Correa, N.Y., O. Li, T. Adali and V. Calhoun, 2005. Comparison of blind source separation algorithms for fMRI using a new Matlab toolbox: GIFT, In: Proceedings of IEEE International Conference on acoustic speech, signal processing (ICASSP), Philadelphia, PA, 5: 401-403.