ISSN 2395-1621

De-noising of magnetic resonance spectroscopy imaging data by using Local low rank filter

#1Pallavi Biswas, #2Priyanka Chavan, #3Neha Kakade, #4S.K.Bhatia

1prbiswas3@gmail.com

#123Student, Dept. of Electronics& Telecommunication Engineering,
#4Professor, Dept. of Electronics& Telecommunication Engineering,

JSPM's ICOER, Pune, Maharashtra, India.

ABSTRACT

An efficient method of magnetic resonance spectroscopic imaging (MRSI) data has been proposed to increase the value of signal-to-noise ratio (SNR) of that MRSI image. A low rank filtering method is proposed for denoising MRSI data is extended to enable local low rank filtering by incorporating tissue boundary constraints ,for low rank model more effective we did integrating B0 field inhomogeneity correction to minimize the rank. The proposed method will be validated using both simulated and in MRSI data for vivo. Its denoising performance is also compared between an upper bound based of the Cramer-Rao constrained lower bound of low-rank filtering. Low rank filtering can effectively improve the SNR of MRSI data corrupted by both noise and B0 field inhomogeneity. The proposed method of low-rank filtering will enhance the utility of high-resolution of MRSI, where SNR has been a limiting factor.

ARTICLE INFO

Article History

Received: 15th May 2017

Received in revised form :

15th May 2017

Accepted: 22nd May 2017

Published online :

23rd May 2017

Key Words: MRSI Image, Local rank Filtering, Gaussian noise, PSNR,MSE.

I. INTRODUCTION

Magnetic resonance spectroscopic imaging (MRSI)[1] is a methode of noninvasive imaging that gives spectroscopic information in addition to the image which is generated by MRI alone. The traditional magnetic resonance imaging (MRI)[2] gives a black-and-white image in that brightness is measured by primarily of T1 or T2 relaxation times of the tissue of imaged, the information of spectroscopic obtained in an MRSI study can be used to in celluar actvity (metabloic information) for further information.

A low-rank filtering is method for a) enable the local low-rank filtering. b) to integrate B0 field inhomogeneity correction[1].Low-rank filtering can effectively improve MRSI data corrupted by noise and B0 field inhomogeneity. This method explains the fact that the multidimensional MRSI signal reside in low dimensional subspaces and shows potential for effective denoising for MRSI data with low SNR.

II. METHODOLOGY

2.1 MRSI Image

Magnetic resonance spectroscopic imaging (MRSI) is for molecular imaging of unique tool. The magnetic resonance spectroscopic imaging(MRSI) data improves the signal-to-noise ratio MRSI data. The MRSI has a metabolic concentration to be performed on a standard MRI scanner ,and the MRSI treatment experience by a patient is the same for MRI. MRSI has huge applications in medicine,with oncology and physiological studies.

The MRSI image of brain is shown below which detect the tumor in brain.

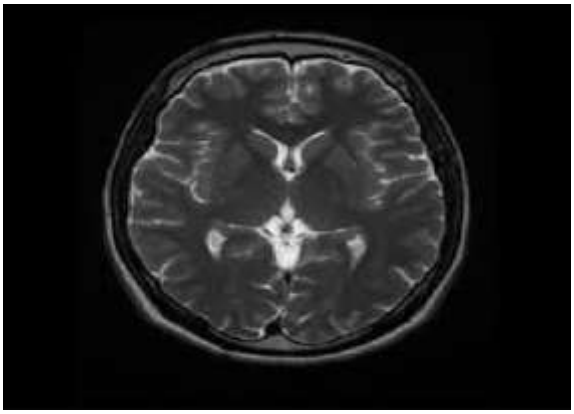

Fig 1 : MRSI Image Of Brain

The is an MRSI input image is not 100% noise free because of certain atmosphere. When it detect the tumor that time it is not accurately detect the tumor because it has a some noise present in that so we proposed a method to remove a 100% noise from that image. We use the low rank filtering. The low rank filtering has two types 1)local rank filtering and 2)global rank filter. We use the local rank filtering to remove the noise from that image.

2.2.Gaussian Noise:

Gaussian noise[2] is having a probability density function (PDF) equal of the normal distribution and it is known as a statistical noise, which is also known as Gaussian distribution. The Gaussian random variable has a PDF which is given by,

$$P_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

The Gaussian noise has a principal sources in digital images generate during acquisition e.g. sensor noise caused by poor illumination and /or high temperature, and/or transition e.g. electronic circuit noise. In digital image processing the spatial filteris used to remove the Guassian noise , though when smoothning an image, undesirable outcome may result in blurring of fine-scaled image edges and details because they also corresponds to blocked high frequencies.

A typical model of image noise is Gaussian, additive, independent at each pixel, and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise), including that which comes from the reset noise of capacitors. Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel.[6] At higher exposures, however, image sensor noise is dominated by shot noise, which is not Gaussian and not independent of signal intensity.

2.3. Local Rank Filtering

The low-rank approximation minimization problem,in which the cost function measures the fit between a given matrix (the data) and an approximation matrix (the optimazation value), subject to a constant that the approximating matrix has reduced rank. The problem for mathematical modelling and data compression.The rank constraints related to a constraints on the complexicity of a model that fits data.

Low rank filters is proposed for denoising practical MRSI data. It exploits the fact that the multidimensional MRSI signals reside in a low-dimesional subspace and shows potential for effective denoising of MRSI data with low SNR.

2.4 Spatial filtering:

Spatial filtering is the effective way for enhancement. It is defined as a neighbourhood and its operation is performed on the pixels inside the neighbourhood. Typically the neighbourhood is much smaller than that of f(x, y) and its size is rectangular. A filtered image is generated as the centre of the mask which moves to every pixel in the input image. It is based on the equation g(x, y) =T [f(x, y)], where T operates on neighbourhood of pixels. There are two types of spatial filtering one is linear and the other is nonlinear. It is linear, when output is weighted sum of input pixels, whereas the method that does not satisfy this property are non linear. For linear spatial filter the response is given by sum of products of filter coefficients and corresponding image pixels spanned by filter.

2.5 Global rank filter:

In the absence of B0 field inhomogeneity and noise, the desired spatiotemporal distribution of an MRSI data set can be modelled by PS function as described by

$$\rho(r,t) = \sum_{l=1}^{L} a_1(r)\psi_1(t) \qquad \cdots (1)$$

Where $(\psi_1(t))$) are a set of temporal basis function ,($a_1(r)$) are the corresponding spatial coefficient and L is the model order of separation rank. LORA exploits the fact that PS fuction induce low-rank matrices in which true signal resides in low dimensional subspace. More specifically, suppose $\rho(r,t)$ in (1) is measured over a set of grids the corresponding Casorati matrix is given by,

$$c(\rho) = \begin{pmatrix} \rho(r_1,t_1) & \rho(r_1,t_2)\cdots & \rho(r_1,t_M) \\ \rho(r_2,t_1) & \rho(r_2,t_2)\ \cdots & \rho(r_2,t_M) \\ \vdots & \vdots \quad \ddots & \vdots \\ \rho(r_N,t_1) & \rho(r_N,t_2)\ \cdots & \rho(r_N,t_M) \end{pmatrix} \qquad \cdots (2)$$

The measured data are corrupted by noise:

$$\hat{p}(r,t) = \rho(r,t) + \in (r,t) \qquad \cdots (3)$$

De-noising is performed by using optimal rank L approximation

$$c^* = argmin||c - \hat{C}(\hat{p})||_F^2 \cdots (4)$$

It is well known that solution to the low-rank approximation in equ(4) can be obtained using singular value decomposition

$$c^* = \sum_{l=1}^{L} \sigma_l u_l v_l^H$$

where σl, ul and vl are the lth singular value, left singular vector, and right singular vector of C(ρˆ), respectively.

III. SOFTWARE DEVELOPMENT

Take an ideal spectra of MRSI (Magnetic Resonance Spectroscopic Imaging) image that is the spectrum of MRSI image.

The noisy spectra of MRSI image which is the spectrum containing with the different noises.

This noisy spectra of MRSI image is de-noised by different low rank filters and we are local low rank filtering method for de-noising.

IV. BLOCK DIAGRAM

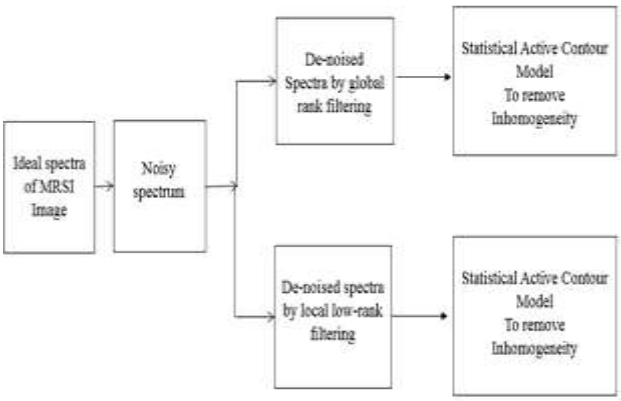

Fig 2. Block diagram

V. RESULT

Take an ideal spectra of MRSI (Magnetic Resonance Spectroscopic Imaging) image that is the spectrum of MRSI image.

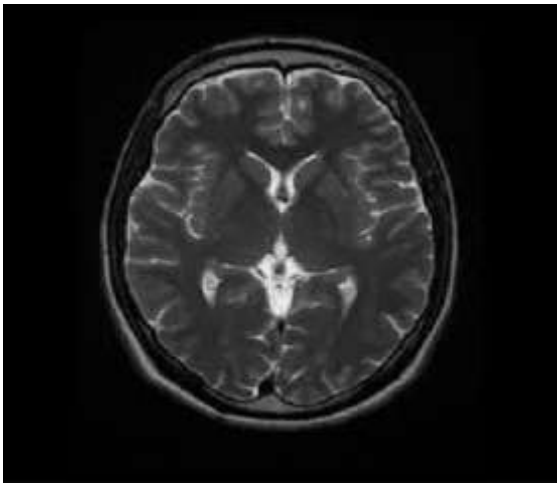

Fig 3: MRSI Image Of Brain

The noisy spectra of MRSI image which is the spectrum containing with the different noises. But we use the Gaussian noise.It is has a better probability density function as well as it is used mostly.

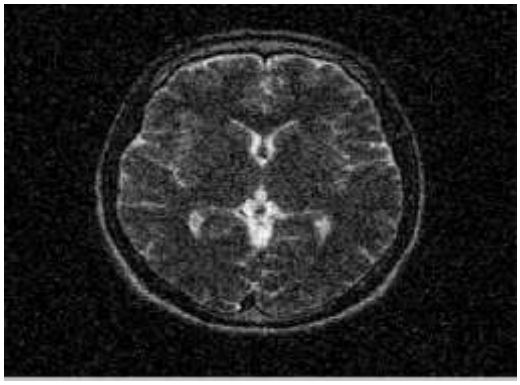

Fig 4: Noise Spectra

This noisy spectra of MRSI image is de-noised by different low rank filters and we are local low rank filtering method for de-noising. The final step its these de-noised MRSI image is given to the statistical active contour model.

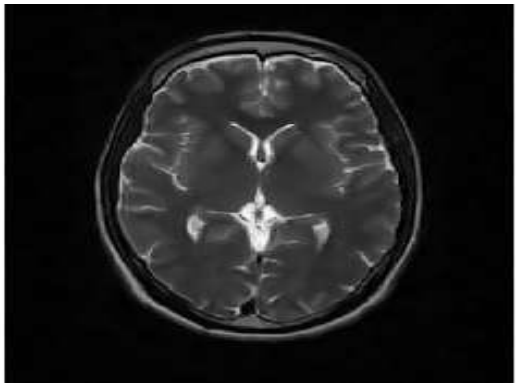

Fig5: Local rank filtering

This image contain the 0% of noise.so we use this image to detect the tumor. Then we calculate the MSE and PSNR value of local rank filtering.

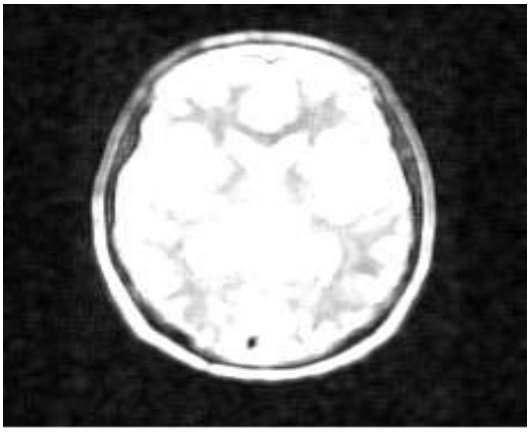

Fig6. Spatial Filter Image

Using spatial filter we remove the noise But the spatial filter is not give the proper result i.e it gives the image which has more brightness so for that reason we can not determine the disease in that image. Spatial It is used in digital image processing. The result of spatial filter.

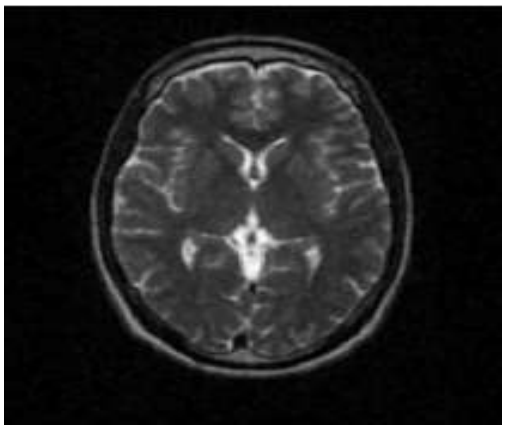

Fig7: Global Rank Filtering Image

The global filter is a type of a low rank filtering. It is not better than the local rank filtering because it is dose not give the actual image or 100% noise free image of MRSI. Result of Global Rank Filtering:

PSNR and MSE values using Gaussian noise:

Filters	PSNR(db)	MSE
Local Filter	81.7620	$4.3294\times e^{-8}$
Global Filter	78.2189	$9.7993\times e^{-4}$
Spatial Filter	-13.1487	0.43616

Table1 : PSNR and MSE Values using Gaussian noise

PSNR and MSE values using Salt and pepper noise:

Filters	PSNR(db)	MSE
Local Filter	70.11378	0.063
Global Filter	67.1656	0.0125
Spatial Filter	50.8853	0.5303

Table2 : PSNR and MSE Values using salt and pepper noise

Contour Models:

Contour models display the edges of image. With the help of contour images we detect the disease or check the noise is 100% remove or not. So the contour model is important for better result analysis.

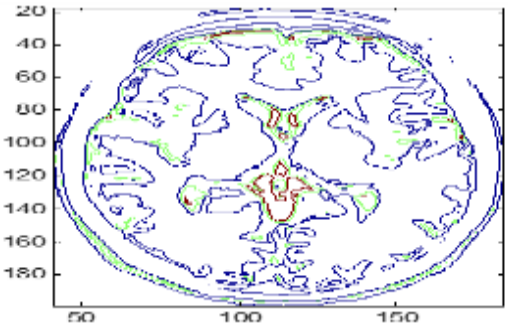

Fig8. Contour Model of Local low rank filtered image

This is the contour model of the local low rank filtering. It shows the proper edges of that brain image. It also show the 100% noise is remove in that so the local rank filtering is used to filter the noisy image of MRSI to detect the disease.

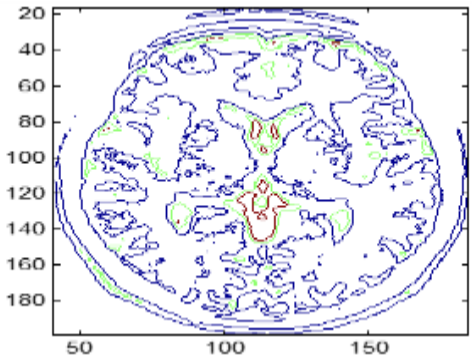

Fig9. Contour Model of Global low rank filtered image

This is the contour model of the global rank filtering. In that it is not give a proper image or actual 100% noise image. So the global rank filter is not better than the local rank filters. So this filter is not used to remove the noise.

VI. CONCLUSION

With the extension of local low rank filtering by incorporating tissue boundary constraints, and these new features improve the performance and robustness of low rank filtering under practical under MRSI conditions, which were demonstrated using simulated and in vivo MRSI data.

Using Low rank filtering, we get the MRSI image which contain 0% noise. This method gives the MSE and PSNR value of that local rank filtering image. This method may prove particularly useful for high-resolution MRSI image ,where SNR is a limiting factor.

VII. ACKNOWLEDGEMENT

We would like to express our deepest appreciation to all those who provided us the possibility to complete this project. A special gratitude we give to our final year project guide, Prof.S.K.Bhatia, whose contribution in stimulating suggestions and encouragement, helped us to coordinate our project, especially in writing this paper.

REFERENCES

1) Yan Liu 1, Member, IEEE, Chao Ma 2, Member, IEEE, Bryan Clifford 3, Student Member, IEEE,Fan Lam 2, Student Member, IEEE, Curtis L. Johnson 2, Member, IEEE, Zhi-Pei Liang 3, Fellow, IEEE," Improved Low-Rank Filtering of Magnetic Resonance Spectroscopic Imaging Data Corrupted by Noise and B0 Field Inhomogeneity"

2) H. F. C. de Greiff et al., “Signal de-noising in magnetic resonance spectroscopy using wavelet transforms,” Concepts Magn. Reson., vol. 14, pp. 388-401, 2002.

3) Y. Bao and A. A. Maudsley, “Improved reconstruction for MR spectro- scopic imaging,” IEEE Trans. Med. Imag., vol. 26, no. 5, pp. 686-695, 2007.

4) H. M. Nguyen et al., “Denoising of MR spectroscopic imaging data with spatial-spectral regularization,” in Proc. IEEE ISBI, 2010, pp. 720-723.

5) D. L. Donoho, “De-noising by soft-threshholding,” IEEE Trans. Inf. Theory, vol. 41, no. 3, pp. 613-627, 1995.

6) X. Hu and Z. Wu, “SLIM revisted,” IEEE Trans. Med. Imag., vol. 12, no. 3, pp. 583-587, 1993.

7) D. C. Noll et al., “Conjugate phase MRI reconstruction with spatially variant sample density correction,” IEEE Trans. Med. Imag., vol. 24, no. 3, pp. 325-336, 2005.

