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An Adaptive Framework for Non-Local MRI Denoising Based On ML Estimation Approach Using Regularizes

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Abstract*— stochastic noise is one of the main causes of quality in magnetic resonance (MR) images, and hence, estimation and removal of noise remains an active area of research. Magnetic Resonance imaging (MRI) without sacrificing spatial resolution, contrast, or scan-time could improve diagnostic value. However, Noise in the MRI can be naturally reduced by averaging complex images after multiple acquisitions. In this paper, a new denoising method based on Maximum Likelihood (ML) estimation methods were proved to be very effective in denoising MR images along with spectral subtraction of the measured noise power from each signal acquisition is presented. The Proposed approach uses an efficient likelihood estimation for image quality Processing. In this approach block Information are used to confirm the quality of Image. The Proposed approach is an adaptive non local ML estimation method for denoising MR images in which the samples are selected in an adaptive way for the ML estimation of the true underlying signal. During acquisition Process some time the k-space is subsampled to increase the acquisition speed (as in GRAPPA like methods), noise becomes spatially varying. The proposed method is capable to denoise multiple-coil acquired MR images. Both the non-central distribution and the spatially varying nature of the noise are taken into account in the proposed method.

***Index Terms*—Maximum Likelihood (ML), Multiple coil, Non-Local Denoising.**

I. INTRODUCTION

Image denoising has been a well studied problem in the field of image processing. Still researchers continue to focus attention on it to give better than the current state-of-the-art. Now many proposed methods take different approaches to solve the problem and yet their denoising performances are comparable. Image denoising is an important image processing effort, both as a process itself, and as a component in other processes. Different ways to denoise an image or a set of data exists. Removes noise while preserving edges which is one of the major properties of a good image denoising [6] [7]. Images are formed by different varieties of physical devices, such as video cameras, x-ray devices, biological microscopes, radar, and ultrasound devices which is used to take the images that are not visible to the human eyes, and used for a variety of purposes, including entertainment, medical applications, business (e.g. documents), industrial, military, civil (e.g. traffic), security, and scientific. The intention in each case for an observer, human or machine, is to extract useful information about the scene being imaged. Images often contain noise, which may arise due to sensor imperfection, poor illumination, or communication errors. Image denoising is an important image processing task, both while acting as a process itself, and also as a component in other processes. Traditionally, Spectral Subtraction has been used [1]. Spectral subtraction method is used to perform denoising on the MR image because it directly applies on the signal and not affect the System. This method is well established for the suppression of additive Gaussian noise. For some purposes this kind of denoising is adequate. One big advantage of spectral subtraction is it efficiently obtain denoising with low computation. But a drawback of the spectral subtraction is it is capable for low compatible device only and it is not capable for high dense noise information. This spectral subtraction may affect the original data during the noise removal. Also, this spectral subtraction is not capable to handle multicoil MR image problem. This method will affect the image quality and is not capable for high compatible devices. In this study, a new denoising method based on Maximum Likelihood (ML) estimation methods were proved to be very effective in denoising MR images along with spectral subtraction of the measured noise power from each signal acquisition is presented. The Proposed approach is an adaptive non local ML estimation method for denoising MR images in which the samples are selected in an adaptive way for the ML estimation of the true underlying signal. In this, we introduce a new, time efficient, image denoising method by applying maximum likelihood method directly to MRI acquisitions in k-space. Maximum likelihood method is simple and capable to handle dense noise image. This method is capable to denoise multiple-coil acquired MR images. Both the non-central distribution and the spatially varying nature of the noise are taken into account in the proposed method. This method is sensitive to maximum kind of information.

II. RELATED WORK

In Wavelet-Based Rician Noise Removal for Magnetic Resonance Imaging [10], Robert D .Nowak explained the filtering methods for Rician noise removal and also derived a novel wavelet-domain filter that adapts to variations in both the signal and the noise. This method provides a simple and effective approach. It reduces the image contrast and it takes low computation. The major drawback in this method is it takes complex program logic for difficult system. Jeny ajan, Ben Jeurissen, Marleen Verhoye, Johan Van Audekerke, Ben Jeurissen, Annemie Van der Linden and Jan Sijbers et al.[4][5][8] proposed a method to denoise magnitude

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magnetic resonance (MR) images, which are Rician distributed. This method estimates the true, underlying signal from a local neighborhood within which the signal is assumed to be constant. The filtering in this approach produces blurred edges and loss of fine structures for the input image. To solve this problem they proposed a concept of restricted local neighborhoods where the true intensity for each noisy pixel is estimated from a set of preselected neighboring pixels. Pietro Perona and Jitendra Malik et al.[9] introduced a class of algorithms that realize it using a diffusion process. The main benefits of this paper are it is the simplest version of anisotropic diffusion and can be applied with success to multiscale image segmentation. Anisotropic Diffusion preserves the edge junctions and the speed of computation is highly perfect. The major drawback of this paper is that the level of Noise varies significantly making the system insufficient to obtain a correct multiscale segmentation. Moreover, anisotropic diffusion can reduce the amount of work. A.Buades, Bartomeu Coll and Jean-Michel Morel [2] explained in their paper "Non-local algorithm for image denoising" to evaluate and compare the performance of digital image denoising methods. In this paper they proposed the concept that the denoising is achieved by averaging all pixels in the image. The major pro in this approach is that it will remove the noise clearly and recover the true images. The major con in this approach is that a small mean square error does not assure a high visual quality. Guido Gerig, Olaf Kubler, Ron Kikinis. and Ferenc A. Jolesz et al.[3] explained this paper based on Anisotropic Diffusion. The major advantage of this method is that it overcomes the blurring of object boundaries and also it increases the signal and reduces the source of noise. The major drawback of this method is inefficiency and loss of resolution.

III. DENOISING MRI USING MAXIMUM LIKELIHOOD ESTIMATION APPROACH

Maximum Likelihood (ML) estimation approaches were proved to be very effective in denoising MR images along with spectral subtraction of the measured noise power from each signal acquisition is presented. The Proposed approach is an adaptive non local ML estimation method for denoising MR images in which the samples are selected in an adaptive way for the ML estimation of the true underlying signal. During acquisition Process some time the k-space is subsampled to increase the acquisition speed, noise becomes spatially varying. The proposed method is capable to denoise multiple-coil acquired MR images. Both the non-central distribution and the spatially varying nature of the noise is taken into account in this method. The block diagram for this approach is defined in fig.1

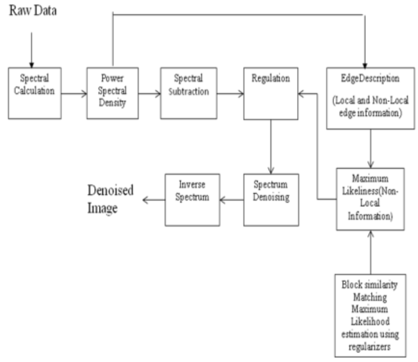

Fig. 1: Flow chart for maximum likelihood estimation approach

A. *Dicom Reader*

Digital Imaging and Communications in Medicine (DICOM) is a tool for handling, printing, storing and transmitting data in medical imaging. It involves a file format definition and a network communication protocol. DICOM has been widely adopted by hospitals in smaller applications like dentists and doctors offices. Fig. 2 shows the working principle of Dicom Reader.

Fig. 2: Dicom Reader

B. Preprocessing

In this module, image is analyzed and preprocessing is employed that include image information calculation such as size, resolution and other aspect of the image that can be used for processing. The input image presents a set of weak features which need to be strengthened so that features can be extracted more accurately. The preprocessing technique used in this paper first converts the raw data into gray scale image based on the parameter such as resolution, size and so on. And it process the gray scale image and produces the result. The preprocessing technique is shown in Fig. 3.

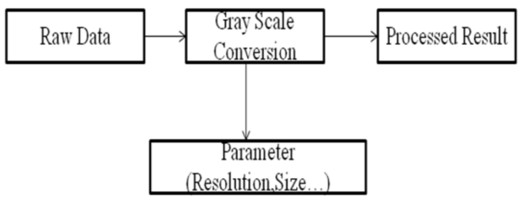

Fig. 3: Preprocessing

C. Spectral Transform

In this paper, the preprocessed result is transformed based on threshold based classification and produces the transformed result [Fig. 4]. The spectral transform method is based on a dual representation of the scalar fields in terms of a truncated series of spherical harmonic functions and in terms of values on a rectangular tensor-product grid whose axes

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represent longitude and latitude. The representation of state variables in spectral space are the coefficients of an expansion in terms of complex exponentials and associated Legendre functions,

$$\xi(\lambda,\mu) = \sum_{m=-M}^{M}\sum_{n=|m|}^{N(m)} \xi_n^m P_n^m(\mu) e^{im\lambda} \qquad (1)$$

Where, $P_n^m(\mu)$ is the associated Legendre function and the spectral coefficients are determined by the equation

$$\xi_n^m = \int_{-1}^{1}\left[\frac{1}{2\Pi}\int_{0}^{2\Pi}\xi(\lambda,\mu)\, e^{-im\lambda}d\lambda\right] P_n^m(\mu)\, d\mu \qquad (2)$$

$$\xi_n^m \equiv \int_{-1}^{1}\xi^m(\mu)\, P_n^m(\mu)\, d\mu \qquad (3)$$

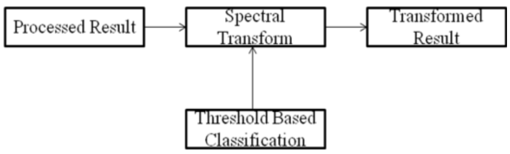

Fig. 4: Spectral Transform

D.Spectral Density Mapping

Spectral density mapping includes the mapping of original information based on the available density. The higher dense information is processed as a group so as the relativeness among the system can be easily grouped and the variational approach can be easily processed [Fig. 5].

D.1. Local Information

Local spectral analysis of images via the two-dimensional continuous wave transformation is employed to trace the local structural based data of the system.

D.2. *Non- Local Information*

No local spectral analysis of images via the two-dimensional continuous wavelet transform is employed to track the local texture based information of the system that can be mapped to increase the overall performance of the system.

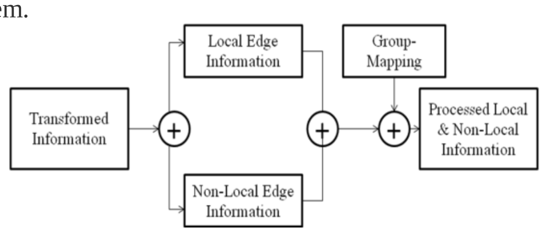

Fig. 5: Spectral Density Mapping Process

E. Spectral Subtraction

E.1. Maximum Likelihood Estimation

The true underlying intensity for each pixel is estimated using the ML estimation method applied on a set of non local (NL) pixels selected based on the intensity similarity of the pixel neighborhood. The number of NL pixels to be considered for ML estimation is fixed and is generally determined in a heuristic way. This fixed sample size can introduce under or over smoothing in the images.

E.2. Adaptive Variance Identifier

This step is based on the threshold information. In this grouped data gets mapped into similar and non-similar structure and identifies the non-similar data for the input image. Fig. 6 show the Spectral Subtraction Process Using Maximum Likelihood (ML) Estimation Approach.

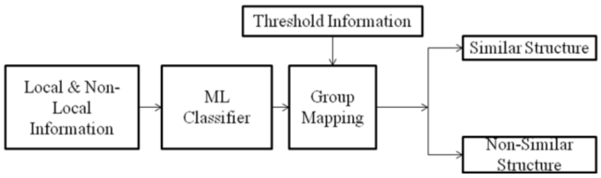

Fig. 6: Spectral Subtraction Process using ML approach

F. K-Space Density Regularizer

The acquired complex signal fills k-space matrix. Each k-space row can be modeled as an underlying true signal plus Gaussian noise.

$$x_r(t) + ix_i(t) = s_r(t) + n_r(t) + i[s_i(t) + n_i(t)] \qquad (4)$$

Where x(t)is the observed k-space signal, s(t)is the true underlying noiseless k-space signal, n(t)is the AGN, and subscripts r and i are denoted as real and imaginary components respectively. For convenience, equations for denoising the real part of any k-space line should be interpreted should also be applied in the imaginary part. The non-similar datas are grouped by similar data is represented in Fig. 7.

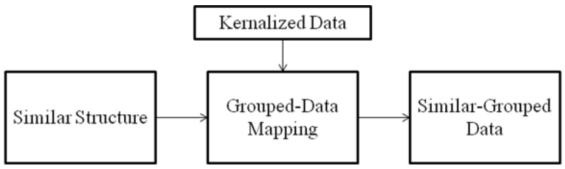

Fig 7: K-Space Density Regularizer

G. Spectral Detransform

In this the similar grouped data gets detransformed to obtain the clear denoised MR Image is shown in Fig.8.

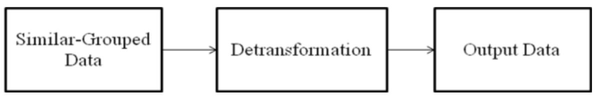

Fig. 8: Spectral Detransform

IV. RESULTS AND IMPLEMENTATION

The output segment is obtained by grouping the non-similar structure to similar structure. And the kernalized data is used for grouped data mapping and produce a similar grouped data. This similar data gets grouped and perform spectrum detransformation to produce the clear denoised MR image. Fig. 9 shows the kernalized data for the input MR image. The kernalized data shows the non-similar data gets

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replaced by similar data for the input image we given. Fig. 10(a) shows the original MR image that we given as input. Fig.10(b) shows the noisy image with SNR 20.174 dB and Fig. 10(c) shows the denoised MR image with SNR 30.0949 dB. The denoised image is obtained by applying the ML method non-locally to the restricted neighborhood.

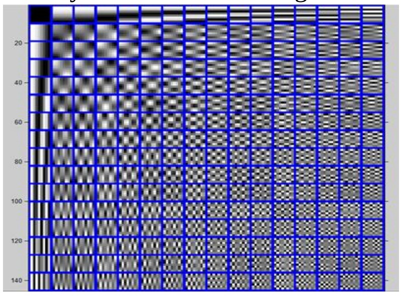
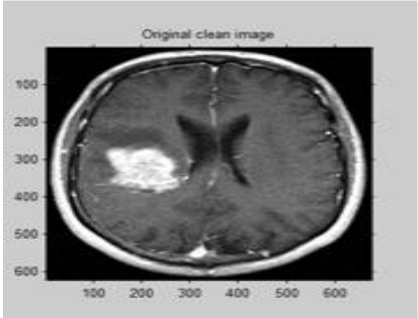
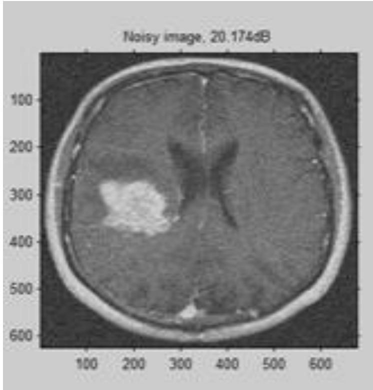


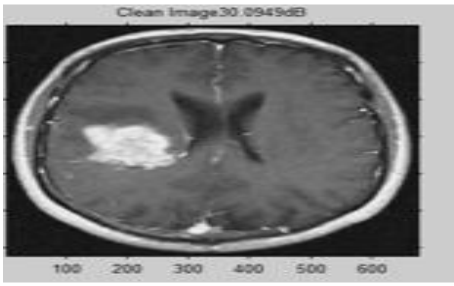
Fig. 9: Kernalized Data



(a)



(b)



(c)

Fig. 10: (a)Original MR Image (b)Noisy MR Image with SNR 20.174dB (c)Clean MR Image with SNR 30.0949 dB

V. DISCUSSION

The Spectral Subtraction method is commonly used in automated speech recognition to improve the estimation efficiency and in many other applications including the temporal denoising of functional MRI (fMRI) data streams for event detection. In existing system, the Spectral Subtraction method is used to perform denoising on the MR image because it directly applies on the signal and not affect the system. This method is well established for the suppression of additive Gaussian noise. One big advantage of spectral subtraction is it efficiently obtain denoising with low computation. But a drawback of the spectral subtraction is it is capable for low compatible device only and it is not capable for high dense noise information. This spectral subtraction may affect the original data during the noise removal. Also, this spectral subtraction is not capable to handle multicoil MR image problem. This method will affect the image quality and is not capable for high compatible devices. In this study, we proposed a new denoising method based on Maximum Likelihood (ML) estimation methods were proved to be very effective in denoising MR images along with spectral subtraction of the measured noise power from each signal acquisition is presented. The Proposed approach is an adaptive non local ML estimation method for denoising MR images in which the samples are selected in an adaptive way for the ML estimation of the true underlying signal. In this, we introduce a new, time efficient, image denoising method by applying maximum likelihood method directly to MRI acquisitions in k-space. Maximum likelihood method is simple and capable to handle dense noise image. This method is capable to denoise multiple-coil acquired MR images. Both the non-central distribution and the spatially varying nature of the noise are taken into account in the proposed method. This method is sensitive to maximum kind of information.

TABLE I: Comparison of signal-to-noise ratio (SNR) for spectralsubtraction and maximum likelihood estimation approach

SNR Image	Spectral Subtraction Method	Maximum Likelihood Estimation Approach
Brain Image1	27.10	30.00
Brain Image2	24.50	29.00
Brain Image3	28.00	34.00

The table 1 shows the comparison result for the signal-to-noise ratio (SNR) for the MRI brain image for spectral subtraction and maximum likelihood estimation approach.The Fig. 11 shows the SNR improvement for the MRI brain images for spectral subtraction and maximum likelihood estimation approach. From this analysis, the maximum likelihood approach provides a better SNR

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improvement than spectral subtraction method and improves the quality of MRI brain image.

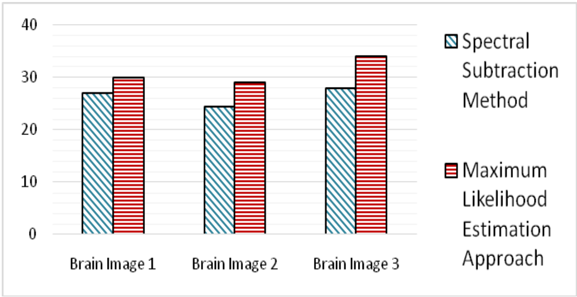

Fig. 11: Comparison of signal-to-noise ratio (SNR) for MRI brain images

VI. CONCLUSION

A new method to denoise MR images by applying the ML method non-locally to restricted neighbourhood is proposed in this paper. A scheme is developed to non-locally select the appropriate subset of pixels from the neighbourhood of each pixel. This method is very effective for denoising MR images along with spectral subtraction of the measured noise power from each signal acquisition is presented.This method is capable to denoise multiple-coil acquired MR images. More over this system is simple and capable to handle dense noise image.ML estimation method is sensitive to maximum kind of information.

REFERENCES

[1] M. Arcan Erturk, Paul A. Bottomley, AbdEl-Monem M. El-Sharkawy ,, "Denoising MRI Using Spectral Subtraction," IEEE Transactions On Biomedical Engineering, Vol. 60, No. 6, June 2013

[2] A. Buades, B. Coll, and J. M. Morel, "A non-local algorithm for image denoising," in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., 2005, vol. 2, pp. 60–65.

[3] G. Gerig, O. Kubler, R. Kikinis, and F. A. Jolesz, "Nonlinear anisotropic filtering of MRI data," IEEE Trans. Med. Imag., vol. 11, no. 2, pp. 221–232, Jun. 1992.

[4] Jeny Rajan, Ben Jeurissen, Marleen Verhoye, Johan Van Audekerke and Jan Sijibers, "Maximum likelihood estimation –based denoising of magnetic resonance images using restricted local neighborhoods," Physics In Medicine And Biology, vol. 56, pp.5221-5234, 2011.

[5] Jeny Rajan, Johan van Audekerke, Annemie Van der Linden, Marleen Verhoye and Jan Sijbers, "An adaptive nonlocal maximum likelihood estimation method for denoising magnetic resonance images," IEEE, vol. 12, 2012.

[6] J. Orchard, M. Ebrahimi, and A. Wong, "Efficient nonlocal-means denoising using the SVD," in Proc. 15th IEEE Int. Conf. Image Process., 2008, vol. 1–5, pp. 1732–1735.

[7] J. V. Manjon, P. Coupe, L. Marti-Bonmati, D. L. Collins, and M. Robles, "Adaptive non-local means denoising of MR images with spatially varying noise levels," J. Magn. Resonance Imag., vol. 31, no. 1, pp. 192–203, Jan.2010.

[8] J. Sijbers, A. J. Den Dekker, J. Van Audekerke, M. Verhoye, and D. Van Dyck, "Estimation of the noise in magnitude MR images," Magn. Resonance Imag., vol. 16, no. 1, pp. 87–90, Jan. 1998.

[9] P. Perona and J.Malik, "Scale-space and edge-detection using anisotropic diffusion," IEEE Trans. Pattern Anal.Mach. Intell., vol. 12, no. 7, pp. 629–639, Jul. 1990.

[10] R. D.Nowak, "Wavelet-based rician noise removal for magnetic resonance imaging," IEEE Trans. Image Process., vol. 8, no. 10, pp. 1408–1419, Oct.1999.

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