International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)
Volume 3, Issue 4, April 2014

Denoising MRI Images Using A Non-Linear Digital Filter

Priyadharsini.B
P.G.scholar, Department of Electronics & communication Engineering,
SNS College of Technology,
Coimbatore,Tamilnadu.

Vanitha.S
Asst.Professor, Department of Electronics & communication Engineering,
SNS College of Technology,
Coimbatore,Tamilnadu.

***Abstract*-Magnetic Resonance Imaging is the best technique used in medical fields for diagnosis of brain tumors at advanced stages. Removing noise from the original MRI is still a challenging problem for researchers. Various approaches are designed and followed for Denoising. A new signal-preserving technique for noise suppression in event-related magnetic resonance imaging (MRI) data is proposed based on spectral subtraction. simple form, the new method does not not change the statistical characteristics of the signal or cause correlated noise. This suggests the new technique as a useful preprocessing step for MRI data analysis. Enhancing Signal-to-noise ratio(SNR) aiding Denoising techniques does not alter the image statistics and its resolution.**

General terms: Digital filter

Keywords: Magnetic Resonance Imaging (MRI),denoising,Spectral subtraction, SNR.

I. INTRODUCTION

In medical imaging, improving signal-to-noise ratio (SNR) in magnetic resonance imaging (MRI) without sacrificing spatial resolution, contrast, or scan-time could improve diagnostic value. $\propto$While time averaging increases SNR, with SNR $\sqrt{}$ (scan-time), extending the scan-time is expensive, prone to motion artifacts, and unacceptable in many clinical MRI applications. Indeed, parallel imaging techniques, such as sensitivity encoding (SENSE) [3] and generalized auto calibrating partially parallel acquisitions (GRAPPA), are commonly used to shorten scan-times. Images reconstructed with these techniques exhibit spatially varying noise statistics, which limit the applicability of conventional denoising techniques.

Several denoising methods have been proposed to enhance the SNR of images acquired using parallel MRI techniques. One method, anisotropic diffusion filtering (ADF), effectively improves SNR while preserving edges by averaging the pixels in the direction orthogonal to the local image signal gradient. ADF can potentially remove small features and alter the image statistics; although adaptively accounting for MRI's spatially varying noise characteristics can offer improvements, this is practically challenged by the unavailability of the image noise matrix [4].Wavelet-based filters have also been applied to MRI [5]–[8]. These are prone to produce edge and blurring artifacts. Recently, denoising methods employing nonlocal means (NLM) [9] were applied to increase the MRI SNR by reducing variations among pixels in the image with close similarity indices [10]. The robustness of the determination of pixel similarity is enhanced by comparing small image regions centered at each pixel, rather than pixel-by-pixel comparisons. While adaptive NLM denoising (involving the estimation and incorporation of spatial variations in the noise power) offers improved performance [11], NLM can still affect image statistics [12] and its computational burden is high compared to other approaches.

In this study, we set up a novel, time competent, image denoising method by applying spectral subtraction directly to MRI acquisitions in *k*-space. Spectral subtraction is well reputable for the suppression of additive Gaussian noise (AGN) and is commonly used in speech processing [13]. It has been applied to the time-course of functional MRI (fMRI) data to facilitate event detection [13], but not the SNR enhancement of routine MRIs.

We test spectral subtraction denoising (SSD) on both numerical simulations, as well as experimental MRI data including parallel SENSE image reconstruction [3], and compare its performance with ADF.

The remainder of the paper is organized as follows: In section II we introduce some related works, in section III we describe about the existing systems and in section IV we propose our technique. Finally, in section V, we give the concluding remarks.

ISSN: 2278 – 909X

II. LITERATURE REVIEW

[2]In medical image processing, medical images are corrupted by diverse type of noises. It is very important to attain accurate images to facilitate precise observations for the application. Removal of noise from medical images is a very exigent issue in the field of medical image processing. Most well recognized noise reduction methods, which are usually based on the local data of a medical image, are not resourceful for medical image noise reduction.

This paper presents an proficient and simple method for noise reduction from medical images. In the future method, median filter is modified by adding more features. Experimental consequences are also compared with the other image filtering techniques. The quality of the output images is measured by the statistical quantity measures: peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) and root mean square error (RMSE). Experimental results of magnetic resonance (MR) image and ultrasound image demonstrate that the proposed algorithm is comparable to popular image smoothing algorithms.

[3]This paper presents a novel method for Bayesian denoising of magnetic resonance (MR) images that bootstrap it by inferring the prior, i.e., the original-image statistics, from the noisy input data and the data of the Rician noise model. The proposed method relies on principle from empirical Bayes (EB) evaluation. It models the prior in a non-parametric Markov random field (MRF) framework and estimates this prior by optimizing an information-theoretic metric with the expectation-maximization algorithm. The overview and power of nonparametric modeling, coupled with the EB approach for former estimation, avoids striking ill-fitting prior models for denoising. The results reveal that, unlike distinctive denoising methods, the proposed method conservse most of the significant features in brain MR images.

Furthermore, this paper presents a novel Bayesian-inference algorithm on MRFs, specifically iterated conditional entropy reduction (ICER). This paper also extends the appliance of the proposed method for denoising diffusion-weighted MR images. confirmation results and quantitative comparisons with the state of the art in MR-image denoising clearly depict the advantages of the proposed method.

The method generalizes in a simple manner to multimodal MR images and vector-valued images. An intrinsic limitation of the nonparametric prior-PDF model is that its performance degrades for image regions not having sufficiently-many repeated patterns. For instance, the proposed method may find it difficult to denoise features/structures that occur rarely in the image because of theoretically-insufficient data to feed into the non-parametric model.

[4]It describe approximate digital implementations of two new mathematical transforms, explicitly, the ridgelet transform and the curvelet transform.These implementations suggest exact renovation, stability against noise, ease of implementation, and low computational complexity. A vital tool is Fourier-domain computation of an approximate digital Radon transform. This introduce a very simple interpolation in Fourier space which takes Cartesian samples and yields samples on a rectopolar lattice, which is a pseudo-polar sampling set based on a concentric squares geometry. Regardless of the crudeness of interpolation, the visual performance is surprisingly good.Ridgelet transform applies to the Radon transform a special over complete wavelet pyramid whose wavelets have dense support in the frequency domain.

Curvelet transform uses ridgelet transform as a component pace, and implements curvelet subbands using a filter bank of wavelet filters. In the tests reported here, simple thresholding of the curvelet coefficients is very competitive with "state of the art" techniques based on wavelets, counting thresholding of decimated or undecimated wavelet transforms and also with tree-based Bayesian posterior mean methods.

Moreover, the curvelet reconstructions reveal higher perceptual excellence than wavelet-based reconstructions, presents visually sharper images and, in particular, higher quality revival of edges and of faint linear and curvilinear features. Existing presumption for curvelet and ridgelet transforms suggests that these new approaches can smash wavelet methods in certain image reconstruction problems.

[6]Magnetic Resonance Image is one of the preeminent technologies currently being used for diagnosing brain cancer at early stages. This paper proposes a novel approach for the MRI image enrichment, which is based on the Modified Tracking Algorithm, Histogram Equalization and Center Weighted Median (CWM) filter. Two approaches introduced are: The first approach is applying the adapted tracking algorithm to eradicate the film perturbations, labels and skull region and then applying the Histogram Equalization and Center Weighted Median (CWM) filter techniques independently to enhance the images**.**

ISSN: 2278 – 909X

III. RELATED WORKS

Several denoising methods have been proposed to enhance the SNR of images acquired using parallel MRI techniques. One technique, anisotropic diffusion filtering (ADF) [2], efficiently improves SNR while preserving edges by averaging the pixels in the direction orthogonal to the local image signal gradient.ADF can potentially remove small features and alter the image statistics, although adaptively accounting for MRI's spatially varying noise characteristics can offer improvements, this is practically challenged by the unavailability of the image noise.

Recently, denoising methods employing nonlocal means (NLM) [9] were applied to increase the MRI SNR by reducing variations among pixels in the image with close similarity indices. The robustness of the determination of pixel similarity is enhanced by comparing small image regions centered at each pixel, rather than pixel-by-pixel comparisons.
While adaptive NLM denoising (involving the estimation and incorporation of spatial variations in the noise power) offers improved performance [11], NLM can still affect image statistics and its computational burden is high compared to other approaches.

Images reconstructed with these approaches exhibit spatially varying noise statistics, which bounds the applicability of conventional denoising techniques.

Also, each filtering technique is prone to particular artifacts in real time analysis. Especially, in Tumor affected MRI scan images, when noise is been removed the characteristics of tumor area is also varied. To avoid this, a novel noise filtering technique is to be adopted whereby SNR value is improved along with preserving the acquired characteristics of tumor maintaining its originality for reliable diagnosis and treatment.

Wavelet-based filters have also been applied to MRI [6]–[10]. These are prone to produce edge and blurring artifacts.

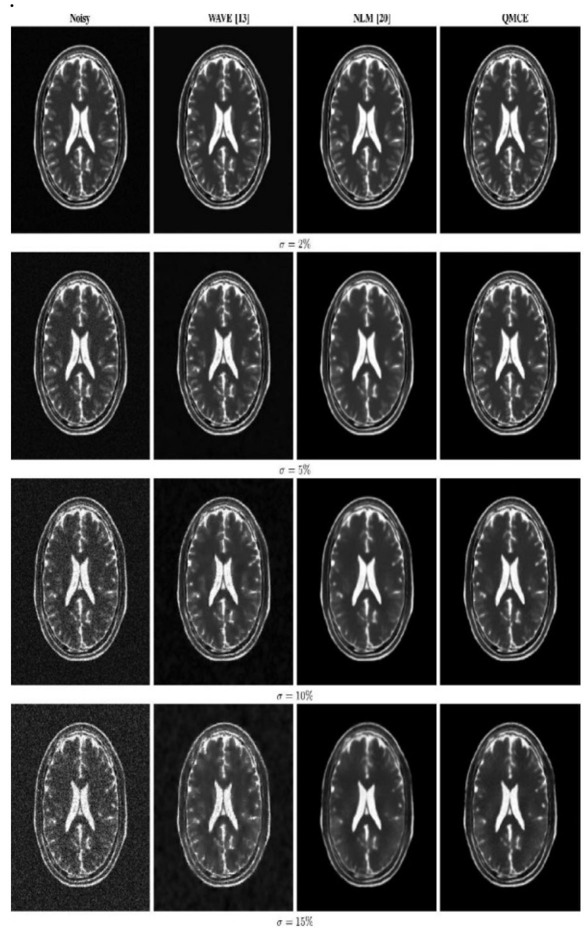

Figure 1: Example of slice of the estimate of the noise-free signal produced by the WAVE [14],NLM [15], and Quasi-Monte Carlo Estimation(QMCE) methods

The above figure 1 shows the slice of estimate for the *T*2 volume at different Rician noise standard deviations.

The signal estimate produced by WAVE contains significant artifacts that relate to the underlying wavelet used. The estimates of the noise-free signals formed by NLM and QMCE do not contain such artifacts and better preserve structural characteristics as well as suppress noise at all noise levels, with QMCE providing an enhancement in sharpness of structural characteristics at high noise levels, principally in the gray matter regions.

4. PROPOSED METHOD

Spectral subtraction methods are generally used in automated speech recognition to improve the estimation efficiency, and in many other applications with the temporal denoising of fMRI data streams for event detection .However, at smallest amount to knowledge, they have not been used in standard MRI for the spatial denoising of individual images. SSD methods work on data corrupted by AGN that is uncorrelated with the underlying data and have a constant power spectrum.

4.1 Computer Simulations

Numerical simulations are carried out using a 1024 × 1024 pixel Shepp–Logan phantom and a reference 256 × 256 pixel high-SNR brain MRI which was measured noise-free [19]. Gaussian noise of the similar amplitude is added to the real and imaginary parts of the 2-D FT (*k*-space) of the images. SSD is applied to the complex *k*-space data, whilst the ADF is applied to the magnitude image. Arithmetical simulations for SENSE [1] images are based on the 256 × 256 high-SNR brain image. Gaussian noise is then added to the real and imaginary parts of the 2-D FT of every eight images.

4.2 Practical Implementation Steps

The subsequent are the steps needed to implement the spectral subtraction denoising process to carry out. Step 1) Choose a spatial area surrounded by the background part of the image exterior the brain away from the Nyquist ghosts and acquire the time courses equivalent to each point within this area. Step 2) Calculate the variance of the intensity values of this area at each time point. Average the estimate from all time points to attain the noise power spectrum level. Step 3) For each point in the image, work out the Fourier transform of its time course and save the phase and magnitude parts of the result individually.

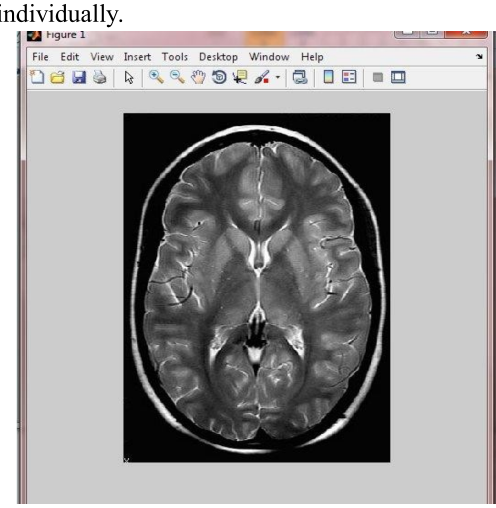

Figure 2: Original MRI

Step 4) Compute the unique power spectrum of this time course using the periodogram method as the square of the magnitude of the Fourier transform in Step 3. Step 5) Calculate the denoised power spectrum by subtracting the noise power spectrum from Step 2.

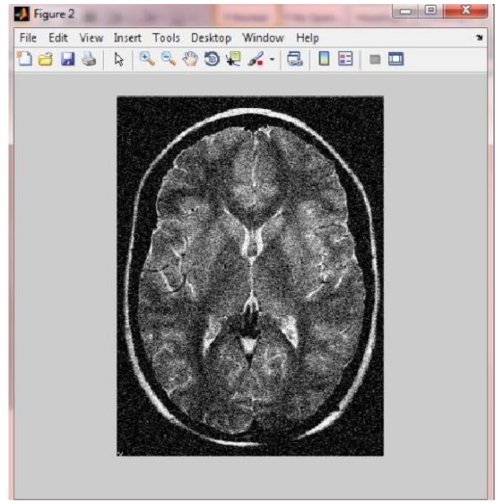

Figure 3: Noisy MRI

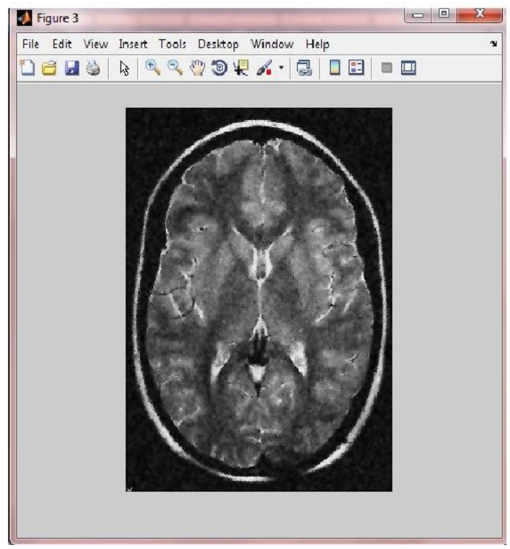

Figure 4: Denoised MRI

The above figure 2,3 & 4 shows the MRI image taken as original, noisy MRI & Denoised using a filter.

The below table shows the PSNR values for Noisy & denoised(filtered) image using bilateral weiner filter

Table 1

Noise	**PSNR with Noise**	**PSNR after Filtering**
10	**28**	**34**
20	**22**	**26.1**
30	**17**	**20**
40	**10.3**	**12.7**

ISSN: 2278 – 909X

5. CONCLUSION

A new signal denoising technique was proposed for MRI signals. The new strategy based on spectral subtraction method is adaptive and simple to implement while offering a substantial improvement of the SNR. The implementation was described and its performance was demonstrated using computer simulations and real data. Further work is needed to investigate the potential of the new technique in different clinical applications. The response of the SSD filter depends on the input signal. It is an SNR-dependent filter wherein lower SNR components are attenuated more than higher SNR components, which may introduce subtle image blurring for low-level signals. The SSD method is immune to such effects when the data acquired from each coil element are separately denoised using its measured average noise power spectrum, which can vary significantly between elements. The present results also suggest that SSD can be applied in situations where there is inherent physiological noise and motion such as in the heart. We have shown SNR improvements of up to 45% for MRI using SSD in both single and array coils reconstruction while preserving image details in simulations and, in practice, in phantoms and multichannel brain and cardiac MRI. The SSD method performs comparably to ADF in terms of SNR improvement, and superior to ADF with respect to accuracy and the preservation of structural feature, at a reduced computational load.

In future, additional to denoising using filters for rician noise and fractional Brownian (Gaussian) noise, deblurring can be performed for further preservation of image characteristics.

REFERENCES

[1] "Denoising using Spectral Subtraction"M. Arcan Ert¨urk, Member, IEEE, Paul A. Bottomley,, and AbdEl-Monem M. El-Sharkawy ,IEEE Transactions on June 2013.

[2] "Regression Models for Identifying Noise Sources in Magnetic Resonance Images", The University of North Carolina at Chapel Hill Department of Biostatistics Technical Report Series, 2007.

[3] K. P. Pruessmann, M. Weiger, M. B. Scheidegger, and P. Boesiger,"SENSE: sensitivity encoding for fast MRI," Magn. Resonance Med.,vol. 42, no. 5, pp. 952–62, Nov. 1999.

[4] M. N. Nobi and M. A. Yousuf "A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images", J. Sci. Res. 3 (1), 81-89 - 2011.

[5] Suyash P. Awate and Ross T. Whitaker, "Feature-Preserving MRI Denoising: A Nonparametric Empirical Bayes Approach Empirical Bayes Approach", IEEE transactions on medical imaging, vol. 26, no. 9, september 2007.

[6] "MRI Brain Image Enhancement Using Filtering Techniques", E. Ben George M.Karnan E. Ben George et al./ International Journal of Computer Science & Engineering Technology (IJCSET).

[7] A. A. Samsonov and C. R. Johnson, "Noise-adaptive nonlinear diffusion filtering of MR images with spatially varying noise levels," Magn. Resonance Med., vol. 52, no. 4, pp. 798–806, Oct. 2004.

[8] S. Aja-Fernandez, C. Alberola-Lopez, and C. F. Westin,"Noise and signal estimation in magnitude MRI and Rician distributed images: a LMMSE approach". IEEE TIP, 17(8):1383–1398, August 2008.

[9] Jean-Luc Starck, Emmanuel J. Candès, and David L. Donoho, "The Curvelet Transform for Image Denoising", IEEE transactions on image processing, vol. 11, no. 6, June 2002.

[10] P. Coup´e, P. Yger, S. Prima, P. Hellier, C. Kervrann, and C. Barillot,"An Optimized Blockwise NonLocal Means Denoising Filter for 3-D Magnetic Resonance Images".IEEE Transactions on Medical Imaging, 27(4):425–441, April 2008.

[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.

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

[12] N. A. Thacker, J. V.Manjon, and P. A.Bromiley, "Statistical interpretation of non-local means," IET Comput. Vis., vol. 4, no. 3, pp. 162–172, Sep. 2010.

[13] Y. M. Kadah, "Adaptive denoising of event-related functional magnetic resonance imaging data using spectral substraction," IEEE Trans. Biomed. Eng., vol. 51, no. 11, pp. 1944–1953, Nov. 2004.

[14] A. Pizurica,W. Philips, I. Lemahieu, and M. Acheroy, "A versatilewavelet domain noise filtration technique formedical imaging," IEEE Trans.Med. Imag., vol. 22, no. 3, pp. 323–331, Mar. 2003.

[15] N. Wiest-Daessl´e, S. Prima, P. Coup´e, S. Morrissey, and C. Barillot, "Rician noise removal by non-local means filtering for low signal-tonoise ratio MRI: Applications to DT-MRI," Med. Image Comput. Comput. Assist. Interv., vol. 11, no. 2, pp. 171–179, 2008.

ABOUT THE AUTHOR

Priyadharsini.B has received B.E degree in Electronics and Communication Engineering from Kalaignar Karunanidhi Institute of Technology, Tamil Nadu in the year 2012. Now she is pursuing M.E (Communication Systems) in SNS College of Technology, Coimbatore,TamilNadu. Her research focuses on performance analysis and Denoising in MRI using filtering techniques.

ISSN: 2278 – 909X