ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

A Novel Noise Filtering Technique for Denoising MRI Images

Priyadharsini.B[1]

PG Scholar, Department of ECE, SNS College of Technology, Chennai Anna University, Tamilnadu, India[1]

ABSTRACT: Magnetic Resonance Image is one of the best technologies currently being used for diagnosing brain tumor at advanced stages. Removing noise from the original MRI is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. 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 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. Improving the signal-to-noise-ratio (SNR) of magnetic resonance imaging (MRI) using denoising techniques could enhance their value, provided that signal statistics and image resolution are not compromised.

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

I. INTRODUCTION

Improving signal-to-noise ratio (SNR) in magnetic resonance imaging (MRI) without sacrificing spatial resolution, contrast, or scan-time could improve diagnostic value.

While time averaging increases SNR, with SNR $\propto \sqrt{}$ (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 introduce a new, time efficient, image denoising method by applying spectral subtraction directly to MRI acquisitions in k-space. Spectral subtraction is well established 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 per se. 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.

II. LITERATURE SURVEY

[2]In medical image processing, medical images are corrupted by different type of noises. It is very important to obtain precise images to facilitate accurate observations for the given application. Removing of noise from medical images is now a very challenging issue in the field of medical image processing. Most well known noise reduction methods, which are usually based on the local statistics of a medical image, are not efficient for medical image noise reduction.

This paper presents an efficient and simple method for noise reduction from medical images. In the proposed method median filter is modified by adding more features. Experimental results are also compared with the other three image filtering algorithms. 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 itself by inferring the prior, i.e., the uncorrupted-image statistics, from the corrupted input data and the knowledge of the Rician noise model. The proposed method relies on principles from empirical Bayes (EB) estimation. It models the prior in a nonparametric Markov random field (MRF) framework and estimates this prior by optimizing an information-theoretic metric using the expectation-maximization algorithm. The generality and power of nonparametric modeling, coupled with the EB approach for prior estimation, avoids imposing ill-fitting prior models for denoising. The results demonstrate that, unlike typical denoising methods, the proposed method preserves most of the important features in brain MR images.

Furthermore, this paper presents a novel Bayesian-inference algorithm on MRFs, namely iterated conditional entropy reduction (ICER). This paper also extends the application of the proposed method for denoising diffusion-weighted MR images. Validation 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 straightforward 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 nonparametric model.

[4]It describe approximate digital implementations of two new mathematical transforms, namely, the ridgelet transform and the curvelet transform. These implementations offer exact reconstruction, stability against perturbations, ease of implementation, and low computational complexity. A central 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 grid, which is a pseudo-polar sampling set based on a concentric squares geometry. Despite 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 compact support in the frequency domain. Curvelet transform uses ridgelet transform as a component step, 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, including thresholding of decimated or undecimated wavelet transforms and also including tree-based Bayesian posterior mean methods.

Moreover, the curvelet reconstructions exhibit higher perceptual quality than wavelet-based reconstructions, offering visually sharper images and, in particular, higher quality recovery of edges and of faint linear and curvilinear

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

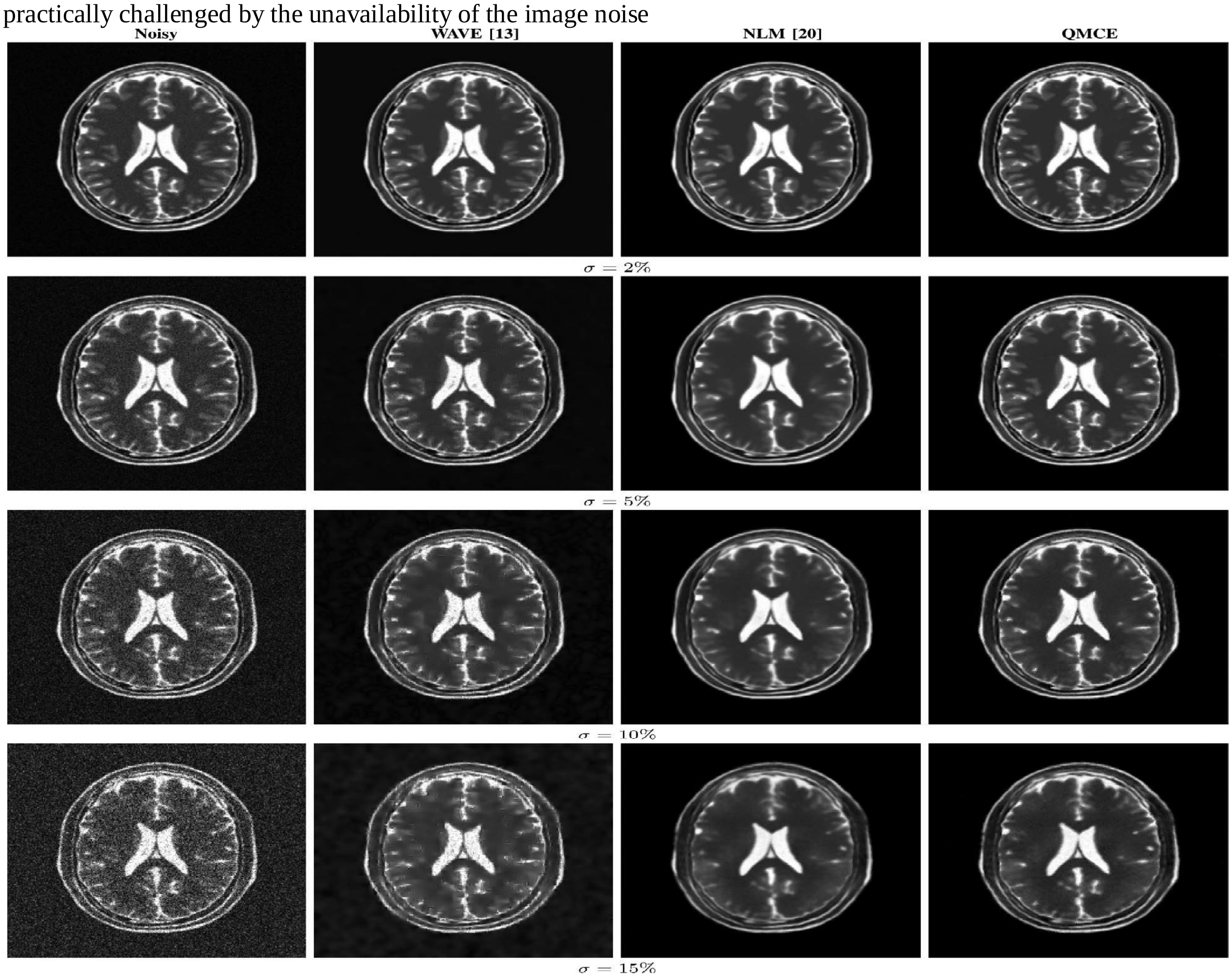
Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

features. Existing theory for curvelet and ridgelet transforms suggests that these new approaches can outperform wavelet methods in certain image reconstruction problems.

[6]Magnetic Resonance Image is one of the best technologies currently being used for diagnosing brain cancer at advanced stages. This paper proposes a novel approach for the MRI image enhancement, which is based on the Modified Tracking Algorithm, Histogram Equalization and Center Weighted Median (CWM) filter. This method consists of two approaches. The first approach is applying the modified tracking algorithm to remove the film artifacts, labels and skull region and then applying the Histogram Equalization and Center Weighted Median (CWM) filter techniques separately to enhance the images**.**

III. RELATED WORKS

Several denoising methods have been proposed to enhance the SNR of images acquired using parallel MRI techniques. One method, anisotropic diffusion filtering (ADF) [2], 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



ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

Fig. 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 for the T2 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 produced 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 improvement in sharpness of structural characteristics at high noise levels, particularly in the gray matter regions.

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 techniques exhibit spatially varying noise statistics, which limit the applicability of conventional denoising techniques.

Also, each filtering technique are 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.

IV. PROPOSED METHOD

Spectral subtraction methods are commonly used in automated speech recognition to improve the estimation efficiency, and in many other applications including the temporal denoising of fMRI data streams for event detection However, at least to our 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 has a constant power spectrum.

Computer Simulations

Numerical simulations are performed using a 1024 × 1024 pixel Shepp–Logan phantom and a reference 256 × 256 pixel high-SNR brain MRI which was considered noise-free [19]. Gaussian noise of the same 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, while the ADF is applied to the magnitude image. Numerical 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 each of the eight images.

Practical Implementation Steps

The following are the steps needed to implement the spectral subtraction denoising procedure in practice. Step 1) Select a spatial area within the background part of the image outside the brain away from the Nyquist ghosts and obtain the time courses corresponding to each point within this area. Step 2) Compute the variance of the intensity values of this area at each time point. Averaging the estimate from all time points to obtain the noise power spectrum level. Step 3) For each point in the image, compute the Fourier transform of its time course and save the phase and magnitude parts of the result separately. Step 4) Compute the original 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) Compute the denoised power spectrum by subtracting the noise power spectrum from Step 2.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) **Vol.2, Special Issue 1, March 2014**

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

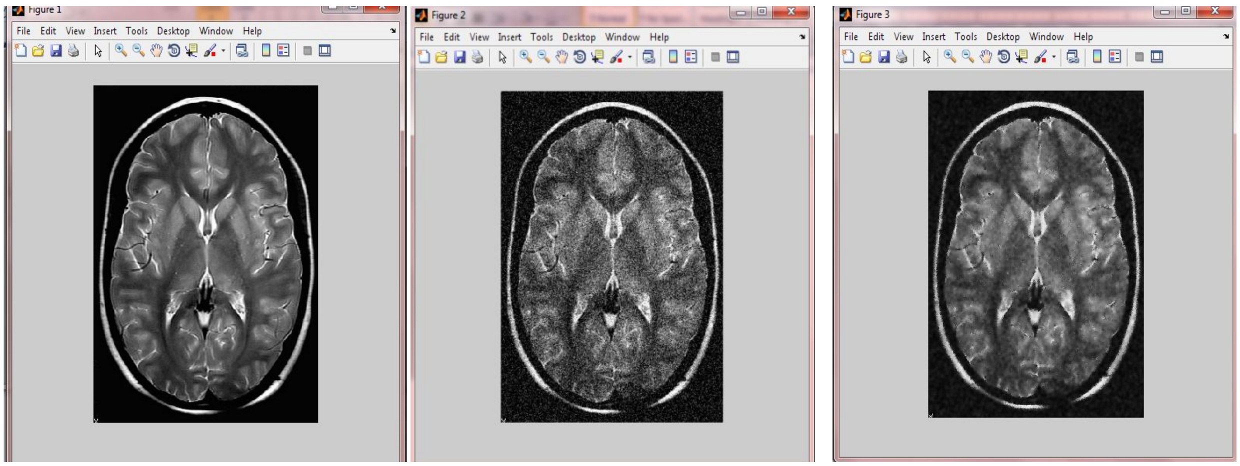


Figure 2-Denoising

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

V. 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 retention of structural detail, 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.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department of CSE, JayShriram Group of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

[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.