The SURE-LET Approach for MR Brain Image Denoising Using Different Shrinkage Rules

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ABSTRACT

SURE-LET Approach is used for reducing or removing noise in brain Magnetic Resonance Images (MRI). Removing or reducing noise is an active research area in image processing. Rician noise is the dominant noise in MRIs. Due to this type of noise, the abnormal tissue (cancerous tissue) may be misclassified as normal tissue and introduces bias into MRI measurements that can have significant impact on the shapes and orientations of tensors in diffusion tensor MRIs. SURE is a new approach to Orthonormal wavelet image denoising. It is an image-domain minimization of an estimate of the mean squared error—Stein’s unbiased risk estimates (SURE). Here, the denoising process can be expressed as a linear combination of elementary denoising processes-linear expansion of thresholds (LET). Different Shrinkage functions such as Soft and Hard and Shrinkage rules and Universal and BayesShrink are used to remove noise and the performance of these results are compared. The algorithm is applied on brain MRIs with different noisy conditions by varying standard deviation of noise. The performance of this approach is compared with performance of the Curvelet transform.

Keywords: Curvelet Transform, Denoising, MRI, Rician Noise, Stein’s Unbiased Risk Estimate (SURE)

1 INTRODUCTION

Medical images are generally of low contrast and they often have a complex type of noise due to various acquisitions, transmission storage and display devices and also because of application of different types of quantization, reconstruction and enhancement algorithms (Sivakumar, 2007). All medical images contain visual noise.

The presence of noise gives an image a mottled, grainy, textured or snowy appearance. Image noise comes from a variety of sources. No imaging method is free of noise, but noise is much more prevalent in certain types of imaging procedures than in others. In magnetic resonance imaging (MRI), there is an intrinsic trade-off between the signal-to-noise ratio (SNR) and resolution (Jiang & Yang, 2003).

In Gupta and Chauhan (n.d.), the author proposes an adaptive threshold estimation method.
for image denoising in the wavelet domain based on the generalized Gaussian distribution (GGD) modeling of subband coefficients. Wang and Zhou (n.d.) proposed a denoising algorithm for medical images based on a combination of the total variation minimization scheme and the wavelet scheme. Wavelet domain filtering is applied to an MRI images in removing noise (Nowak, 1999; Nowak, Gregg, Coopery, & Sieberty, n.d.). In Starck, Candes, and Donoho (2002), Curvelet transform and Ridgelet transform are used to remove noise from the natural image. In Zhang, Fadili, and Starck (2008), the author proposed a method to remove the poisson noise in natural images using wavelet, Ridgelet and Curvelet. The superiority of Curvelet transform in medical image denoising is proved in Parthiban and Subramanian (2006). Luisier and Blu proposed SURE Approach for removing Gaussian noise in natural images (Blu & Luisier, 2007; Luisier, Blu, & Unser, 2007). In this work, the SURE-LET Approach is used for removing Rician noise in MRI brain images. For comparative study, Curvelet transform also used for same purpose.

The paper is organized as follows. First, in Section II, the Noise in MRI is dealt. Proposed Methodology is discussed in Section III, the SURE-LET Approach is described in Section IV and Curvelet Transform for denoising is described in section V. Results and Discussion are dealt in section VI. Finally, conclusions are given in Section VII.

2. NOISE IN MRI

The main source of noise in MRI images is the thermal noise in the patient. This type of noise is due to thermal vibrations of ions and electrons and movement of objects during acquisition. MR images are obtained by taking inverse discrete Fourier Transform. While doing this, the real and imaginary channels are affected by white Gaussian noise. So magnitude of the image is always taken for both visual inspection and computer analysis. The image data now follows Rician distribution which is Rician noise. The term Rician noise is used to refer the error between the underlying image intensities and the observed data. Rician noise is not zero-mean and the mean depends on the local intensity in the image. For high signal-to-noise ratio (SNR) fMRI data, Rician distributed noise is symmetric, thus, can be considered as Gaussian distributed. For low SNR fMRI data, there is a difference between Gaussian and Rician distributed noise, i.e., an image with low intensity and Rician distributed has probability density which is asymmetric (Asefa, Mital, Haque, & Srinivasan, n.d.). Low resolution imaging (resolutions commonly used in clinical practice) is quite useful in many applications. One advantage of low resolution, high SNR imaging is that the noise is accurately approximated as Gaussian white noise. Gaussian noise removal is fairly straightforward and hence low resolution, high SNR images can be improved using a variety of noise filtering techniques. However, the Gaussian noise model is only an approximation. In high resolution, low SNR imaging the Gaussian approximation is inaccurate. Moreover, noise removal in low SNR imaging is even more crucial than it is in high SNR cases (Gregg & Nowak, 1997). A practical consequence is a reduced image contrast: noise increases the mean value of pixel intensities in dark image regions because of this complication, magnetic resonance image estimation from noisy data is especially challenging.

In Rice distribution, the real and imaginary data, with mean values $A_r$ and $A_i$ respectively, are corrupted by zero mean Gaussian, stationary noise with standard deviation $\sigma$, it is easy to show that the PDF of the magnitude data will be a Rician distribution given by Sijbers, Dekker, Van Audekerke, Verhoye, and Van Dyck (1998):

$$p_M[M/A] = \frac{M}{A^2} e^{-\frac{M^2 + A^2}{2A^2}} I_0 \left(\frac{AM}{\sigma^2}\right) (1)$$
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