REMOVING OF RICIAN NOISE USING WAVELET IN MAGNETIC RESONANCE IMAGES

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***ABSTRACT—**Medical procedures have become a critical application area that makes substantial use of image processing. Medical image processing tasks mainly deal with improvement of image quality i.e., Filtering, sharpening, enhancement. The interdisciplinary area of digital signal and image processing forms a basis for de-noising, enhancement, recovery and classification of biomedical images. Many magnetic resonances (MR) Images obtained directly by the instruments are not satisfied by doctors. For example, there are some noises like rician noise and poor contrast in the MR images. Wavelet expansions and wavelet transforms have proven to be very efficient and effective in analyzing a very wide class of signals and phenomena. Wavelet expansion allows a more accurate local description and separation of signal characteristics. In this paper, we propose a wavelet domain method for noise filtering and restoration of MRI images. The goal of this paper is to investigate the discrete wavelet transform (DWT) and its application to MRI image denoising.*

Keywords-Wavelet Trasform, MRI, Image Denoising, Thresolding Method Of Denoising

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a medical imaging technique that has proven to be particularly valuable for examination of the soft tissues in the body.MRI is an imaging technique that makes use of the phenomenon of nuclear spin resonance. Since the discovery of MRI, this technology has been used for many medical applications. Because of the resolution of MRI and the technology being essentially harmless it has emerged as the most accurate and desirable imaging technology [1]. MRI is primarily used to demonstrate pathological or other physiological alterations of living tissues and is a commonly used form of medical imaging. Despite significant improvements in recent years, magnetic resonance (MR) images often suffer from low signal-to-noise ratio (SNR) or contrast-to-noise ratio (CNR), especially in cardiac and brain imaging. Therefore, noise reduction techniques are of great interest in MR imaging as well as in other imaging modalities.

The concept of image restoration differs significantly from the idea of image enhancement. While enhancement aims at improving the appearance of the image or its properties with respect to the following analysis (by a human operator or even automatic), the goal of restoration is to remove an identified distortion from the observed image, thus providing (in a defined sense) the best possible estimate of the original undistorted image.[2] The observed image may be distorted by blur, geometrical deformation and non linear contrast transfer.

The noise in MRI obeys a rician noise distribution. It is signal dependent and consequently separating signal from the noise is difficult task. Rician noise is especially problematic in low SNR images. It also introduce signal dependent bias to the data that reduces image contrast. The rician corrupted data is given by equation.

$$s = \sqrt{\left(\frac{x}{\sqrt{2}} + n_r\right) + \left(\frac{x}{\sqrt{2}} + n_i\right)}$$

(1)

Where n_r and n_i ~ (0, σ2). The value s is the realisation of a random variable with a Rician p.d.f. with parameters x and σ.

In de-noising, single orthogonal wavelets with a single-mother wavelet function have played an important role. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. Crudely, it states that the wavelet transform yields a large number of small coefficients and a small number of large coefficients. Simple de-noising algorithms that use the wavelet transform consist of three steps.

- Calculate the wavelet transform of the noisy signal.
- Modify the noisy wavelet coefficients according to some rule.
- Compute the inverse transform using the modified coefficients.

One of the most well-known rules for the second step is soft thresholding. Due to its effectiveness and simplicity, it is frequently used in the literature. The main idea is to subtract the threshold value T from all wavelet coefficients larger than T, arising from the standard discrete wavelet transform and to set all other coefficients to zero.

The problem of Image de-noising can be summarized as follows. Let $x(m,n)$ be the noise-free image and $\hat{x}(m,n)$ be the image corrupted with independent Gaussian noise $z(m,n)$.

$$\hat{x}(m,n) = x(m,n) + \sigma z(m,n) \qquad (2)$$

where $z(m,n)$ has normal distribution $N(0,1)$.

The problem is to estimate the desired signal as accurately as possible according to some criteria. In the wavelet domain, if an orthogonal wavelet transform is used, the problem can be formulated as

$$\hat{x}(m,n) = w(m,n) + N(m,n) \qquad (3)$$

where $\hat{x}(m,n)$ is noisy wavelet coefficient; $w(m,n)$ is true coefficient and $N(m,n)$ noise, which is independent Gaussian. . In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighbourhood on the performance of image de-noising algorithms in terms of PSNR.

II. PRINCIPLES OF DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT) of image signals produces a non-redundant image representation, which provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Gaussian and Laplacian pyramid. Recently, Discrete Wavelet Transform has attracted more and more interest in image de-noising [3]. The DWT can be interpreted as signal decomposition in a set of independent, spatially oriented frequency channels. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in figure 1. These are also known by other names, the sub-bands may be respectively called a^1 or the first average image, h^1 called horizontal fluctuation, v^1 called vertical fluctuation and d^1 called the first diagonal fluctuation. The sub-image a^1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The Gaussian noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be threshold.

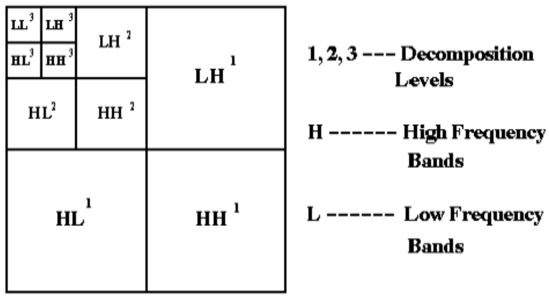

Figure 1: 2D-DWT with 3-Level decomposition

III. WAVELET THRESHOLDING

Image denoising algorithm attempts to remove this noise from the image. Ideally, the resulting de-noised image will not contain any noise or added artifacts. De-noising of natural images corrupted by Gaussian noise using wavelet techniques is very effective because of its ability to capture the energy of a signal in few energy transform values. The methodology of the discrete wavelet transform based image de-noising has the following three steps as shown in figure 2.

1. Transform the noisy image into orthogonal domain by discrete 2D wavelet transform.
2. Apply hard or soft thresholding the noisy detail coefficients of the wavelet transform
3. Perform inverse discrete wavelet transform to obtain the de-noised image.

Here, the threshold plays an important role in the denoising process. Finding an optimum threshold is a tedious process. A small threshold value will retain the noisy coefficients whereas a large threshold value leads to the loss of coefficients that carry image signal details.

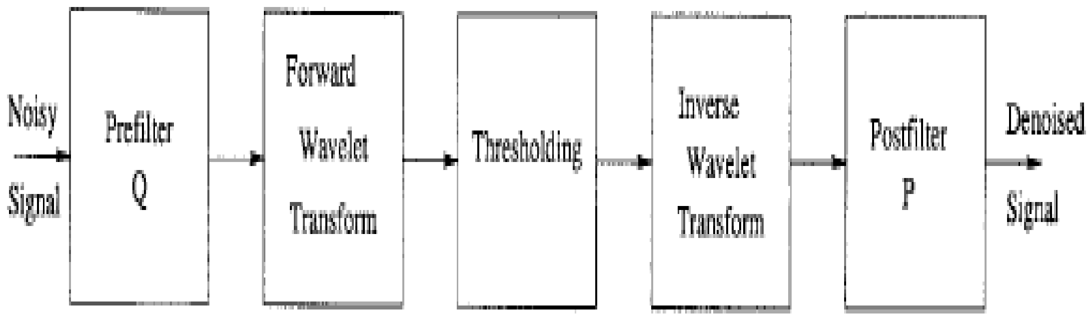

Figure2: Diagram of wavelet based image De-noising

A common approach for image de-noising is to convert the noisy image in to a transform domain such as wavelet and then compare the transform coefficients with a fixed threshold [3].
A number of wavelet thresholding techniques were considered for comparing the results with the proposed methods. They are briefed below.

Denoising based on threshold of wavelet transform

The basic theory for the thresholding of the wavelet of wavelet coefficients is supposing that there are a number of wavelet coefficients which are polluted seriously very small or near zero. So a threshold can be used to remove the polluted points in order to remove the noise.
This threshold may be divided in two categories:

• Soft threshold: The soft threshold makes the model which is smaller than the threshold of the wavelet coefficients replaced by zero [4].
The soft thresholding operator is defined as:

$$y = sign(x)(|x| - T) \quad (4)$$

• Hard threshold: the hard threshold retains the model whose value is greater than the threshold of wavelet coefficients, and makes the model whose value is smaller than the threshold [1].
The hard threshold operator is defined as:

$$y = x \text{ if } |x| > T$$
$$y = 0 \text{ if } |x| < T \quad (5)$$

where x is the input signal, y is the signal after threshold and T is the threshold level.

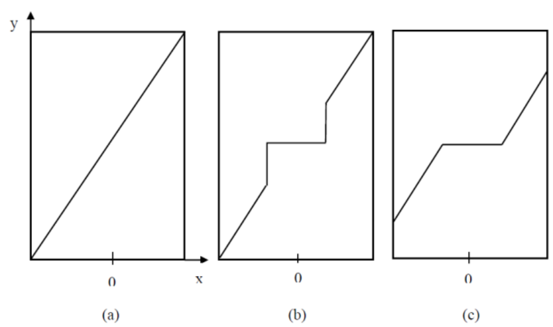

Fig. 3 Threshold types: (a) Original signal; (b) Hard; (c) Soft

The hard type does not affect the coefficients that are greater than the threshold level, whereas the soft type causes shrinkage to these coefficients. In the present work, both types of threshold are evaluated but hard thresholding may create abrupt artifacts because of its discontinuous nature. The reconstructed image is a de-noised estimate of x, which is produced by the inverse DWT.

$$\hat{x} = w^{-1}\hat{y} \quad (6)$$

Where $\hat{y}$ consists of the threshold sub bands of the noised image. The threshold level is estimated by various methods called thresholding criteria, which are based on the minimization of the averaged squared error.

$$\arg\min\left[\frac{1}{N}\sum_i\left(\hat{Y}_i - X_i\right)^2\right]$$

(7)

Where X_i and $\hat{Y}_i$ are all the detail sub bands coefficients of the original image and the noised image after thresholding respectively.

Denoising based on Bayesian threshold

Based on the Bayes rule this is another technique to find out the threshold for image de-noising in the wavelet domain. Bayes Rule allows us to write the expression for the estimated image in terms of probability densities of the noise and signal.[7]
The threshold equation is given as:

$$\hat{T}_B\left(\hat{\sigma}_X\right) = \frac{\hat{\sigma}^2}{\hat{\sigma}_X} \quad (8)$$

The Bayesian threshold described above provides a natural extension for incorporating the higher order statistical regularity present in the statistics of sub band representations.

IV. PROPOSED DENOISING APPROACH

For image denoising, first apply 2 D wavelet transform. At every decomposition level, we get four frequency subbands, namely, LL, LH, HL, and HH. The next level should be applied to the low frequency subband LL only. This process is continued until a pre specified level is reached.

Since the noise will be nearly averaged out in the low frequency wavelet coefficients and we want to keep small coefficients in these frequencies, only wavelet coefficients in the high frequency levels need to be threshold. That means we need to threshold all LH, HL, and HH within these high frequency sub bands. For every wavelet coefficient of our interest, we need to consider a neighbourhood Window *B* Around it. We choose the window by having the same number of pixels above, below, and on the left or right of the pixel to be thresholded. That means the neighbourhood window size should be 3 × 3, 5 × 5, 7 × 7, etc. Figure illustrates a 3 × 3 neighbourhood window centered at the wavelet coefficient to be thresholded. We threshold different wavelet coefficient subbands independently.

When the above summation has pixel indices out of the wavelet subband range, we omit the corresponding terms in the summation. For the wavelet coefficient to be thresholded, we shrinkage it according to the following formula:

$$\hat{\theta}_{ij} = w_{ij}\beta_{ij}$$

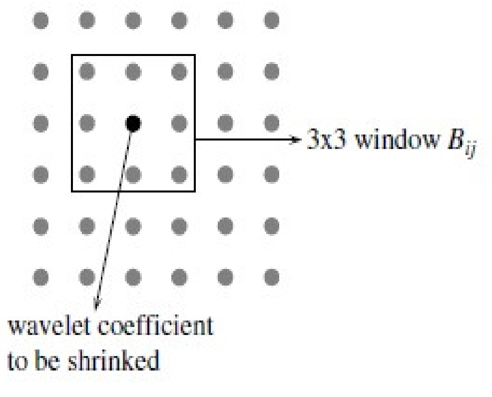

Fig. 4 Concept of Window Selection

Where the shrinkage factor can be defined as:

$$\beta_{ij} = \left(1 - \frac{\lambda^2}{S_{ij}^2}\right)$$

$$S_{ij}^2 = \sum\nolimits_{k,l \in \beta_{ij}} w_{kl}^2$$

The neighbourhood window size around the wavelet coefficient to be threshold has influence on the denoising ability of our proposed algorithm. The larger the window, the relatively smaller the threshold is. If the size of the window around the pixel is too large, a lot of noise will be kept, so an intermediate window size of 3 × 3 or 5 × 5 should be used.

V. PERFORMANCE PARAMETER

Traditionally, image quality has been evaluated by human subjects. This method, though reliable, is expensive and too slow for real world applications, so there is computational models that can automatically predict perceptual image quality which known as image quality assessment techniques. Where $x(m,n)$ denotes the samples of original image, $\hat{x}(m,n)$ denotes the samples of distorted image. Where *M* and *N* are number of pixels in row and column directions, respectively, the techniques that used to assess the quality of images are:

1. Mean Square Error (MSE)

The simplest of image quality measurement is Mean Square Error (MSE). The large value of MSE means that image is poor quality. MSE is defined as follow:

$$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(x(m,n) - \hat{x}(m,n)\right)^2$$

(9)

2. Peak Signal to Noise Ratio (PSNR):

A high quality image has small value of Peak Signal to Noise Ratio (PSNR). PSNR is defined as follow:

$$PSNR = \left[10 Log \frac{255^2}{MSE}\right] \quad (10)$$

3. Correlation Coefficient

Correlation Coefficient gives value of correlation between original and targeted image. If Correlation Coefficient is nearer to 1 then original and targeted images are tends to identical and vice-versa if Correlation Coefficient is nearer to 0.

$$Co.C(\beta) = \frac{\sum\left(g - \bar{g}\right)\left(\hat{g} - \bar{g}\right)}{\sqrt{\sum\left(g - \bar{g}\right)^2 \sum\left(\hat{g} - \bar{g}\right)}}$$

VI. EXPERIMENTS AND RESULT

The above image de-noising methods were applied to a MRI image. The noisy image was applied discrete wavelet transformed. The threshold estimation is either detail or sub band level dependent. The proposed methods are tested for various thresholding criteria and use soft thresholding to provide smoothness and better edge preservation, avoiding the discontinuity character of the hard thresholding methods. The better result obtained using Bayes Thresholding method. The best result obtained using Proposed Algorithm. The results are compared on the basis of PSNR, MSE, and Correlation coefficient. The restored MRI image having better contrast then noisy Image. The respective values are listed in the table below:

	MSE	PSNR	Co.C
Noisy Image	584.33	20.46	0.89
Soft thresholding	161.87	26.03	0.960
Hard Thresholding	153.49	26.26	0.969
Bayes Thresholding	113.9	27.56	0.97
Proposed Algorithm	104.5	27.92	0.98

Table: 1 RESULT FOR DIFFERENT DENOISING METHODS

Fig. 5 Original Image

Fig. 6 Noisy Image (Rician Noise)

Fig. 7 Denoised Image using Soft Thresholding

Fig. 8 Denoised Image using Hard Thresholding

Fig. 9 Denoised Image using Bayes Thresholding

Fig. 10 Denoised Image using Proposed Algorithm

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