WAVELET BASED THRESHOLDING FOR IMAGE DENOISING IN MRI IMAGE

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ABSTRACT

In medical image processing, image denoising plays very vital role in all through the diagnose. Removing noise from the original signal is still a bottleneck problem for researchers. There have been various denoising techniques; each has its own assumptions, advantages, and limitations. The main aim of Image denoising is to recover signal to be as close as possible to the original signal, while retaining its most important features and quality as much as possible. This paper proposes different approaches of wavelet based image denoising methods. Magnetic resonance imaging (MRI) are routinely used for medical diagnosis. Denoising of these images to enhance their quality and clinical parameter for an active area of research. This paper presents the wavelet-based thresholding scheme image denoising and noise suppression in MRI images. The performance of denoising scheme is evaluated in terms of the peak signal to noise ratio (PSNR), the mean square error (MSE) and the mean absolute error (MAE).

Keywords: Wavelet, Decomposition, MRI, Thresholding.

I. INTRODUCTION

Magnetic Resonance imaging is a widely used in medical imaging procedure because it is comparatively safe, transferable, and adaptable. Though, one of its main shortcomings is it involve really loud noise while processing because they involve a really high amount of electric current supply.

Estimating a signal that is corrupted by noise has been of interest to many researchers for practical as well as theoretical reasons. The purpose is to recover the original signal from the corrupted or noisy data. The main aim of image denoising techniques is to recover signal to be as close as possible to the original signal.
Traditional denoising schemes are based on linear methods, where the most common choice is the Wiener filtering. Recently, nonlinear methods, especially those based on wavelets have become increasingly popular [1].

One of the earliest research paper in the field of image denoising is wavelet-based denoising [1]. A new method for filtering noise from MRI images based on the thresholding scheme. Using wavelet-thresholding, the noise could be significantly reduced without reduce the edge sharpness [2]. Wavelet shrinkage has many excellent properties, such as near optimality in minimax sense, and a better rate of convergence [3][4].

Besides wavelet-thresholding, many other approaches have been suggested as well. Wavelet-based denoising using Hidden Markov Trees [HMT], has been quite successful, and it gave rise to a number of other HMT-based schemes [6]. Even though much work has been done in the field of wavelet thresholding, most of it was focused on the statistical modeling of wavelet coefficients for a certain class of signals (e.g. natural images), and the optimal choice of the threshold values.

During acquisition of MRI images are mostly corrupted by noise. Also, noise may be produced because of imperfect instrument used during processing, interference and compression [7]. Image noise can be defined as random variation of brightness or color information image produced by the sensor and circuitry of the scanner. Noise in MRI poses a lot of problem to MRI diagnosis and treatment of human. Image noise in large measures contributes high hazards faced by human [8]. In the digital images like MRI, noise are low as well as high frequency components.

The great challenge of image denoising is how to preserve the edges and all fine details of an image while suppression of noise. It still remains challenge for researchers as noise removal introduces artifacts and causes blurring of the images. So, it is necessary to develop an efficient denoising technique to avoid such data corruption.

In this research paper, a new thresholding function is developed to improve the denoised results of MRI images. Experimental results are given and quantified in terms of PSNR, MSE & MAE and the quality of image show the advantage of the proposed method.
II. 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.

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 a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. The sub-image a1 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 [9].

![Figure 1: Two-Level Image decomposition by using DWT](image-url)
III. METHODOLOGY

The reduction of noise present in images is an important aspect of image processing. Denoising is a procedure to recover a signal that has been corrupted by noise. After discrete wavelet decomposition the resulting coefficients can be modified to eliminate undesirable signal components. To implement wavelet thresholding a wavelet shrinkage method for de-noising the image has been verified. The proposed algorithm to be used is summarized in Algorithm 1 and it consists of the following steps.

Wavelet image de-noising

Step 1: Choice of a wavelet (e.g. Haar, symmlet, etc) and number of levels or scales for the decomposition. Computation of the forward wavelet transform of the noisy image.

Step 2: Estimation of a threshold.

Step 3: Choice of a shrinkage rule and application of the threshold to the detail coefficients.

Step 4: Application of the inverse transform (wavelet reconstruction) using the modified (threshold) coefficients.

![Flowchart for Image Denoising Algorithm Using Wavelet Transform](image.png)

**Figure 2:** Flowchart for Image Denoising Algorithm Using Wavelet Transform
IV. THRESHOLDING TECHNIQUE

Thresholding is the simplest method of image denoising. In this from a gray scale image, thresholding can be used to create binary image. Thresholding is used to segment an image by setting all pixels whose intensity values are above a threshold to a foreground value and all the remaining pixels to a background value.

In the application of De-noising, the threshold level parameter $T$ plays an essential role. Values too small cannot effectively get rid of noise component, while values too large will eliminate useful signal components. There are a variety of ways to determine the threshold value $T$ as we will discuss in this section Depending on whether or not the threshold value $T$ changes across wavelet scales and spatial locations, the thresholding can be:

**Global Threshold:**

The global threshold method derived by Donoho is given by Eq. (1) has a universal threshold:

$$\lambda = \sigma \sqrt{2\log(N)}$$

(1)

Where $N$ is the size of the coefficient arrays and $\sigma^2$ is the noise variance of the signal samples.

V. PERFORMANCE EVALUATION

To get the measure of the wavelet performance, the experimental results are evaluated according to three error criteria namely, the mean square error (MSE), the mean absolute error (MAE) and the peak signal to noise ratio (PSNR).

1. **Peak signal to Noise Ratio (PSNR):** PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the quality and reliability of its representation. It defines the purity of the output signal. PSNR is calculated as follows:

$$PSNR = 10 \log_{10} \left( \frac{MAX^2_i}{MSE} \right)$$
\[=20 \log_{10} \left( \frac{MAX}{\sqrt{MSE}} \right) \quad (2)\]

Where, MSE = Mean Squared Error, MAXI is the maximum possible pixel value of the image.

2. **Mean Squared Error (MSE)**: Mean Square Error (MSE) function is commonly used because it has a simple mathematical structure that is easy to compute and it is differentiable implying that a minimum can be sought. The MSE is the difference between the original image and the denoised image. Given by

\[MSE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (y(m,n) - \hat{y}(m,n))^2 \quad (3)\]

3. **Mean of absolute error (MAE)**: Another criterion measure include: Mean of absolute error (MAE) which is given by

\[MAE = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} |y(m,n) - \hat{y}(m,n)| \quad (4)\]

The goal of de-noising is to find an estimate image such that MAE is minimum.

**VI. RESULTS AND DISCUSSION**

For our test experiments we have considered an additive noise with a uniform distribution which has been used to corrupt our simulated and real MR test image objects. Artificially adding noise to an image allows us to test and assess the performance of various wavelet functions.

**Figure 3**: (a) Original image and (b) Noisy image

Here the brain MRI was decomposed using the 4-level decomposition as shown below.
Figure 4: Level 1, 2, 3 and 4 image decomposition

Figure 5: Denoised Image
We used MATLAB to implement. A usual way to de-noise is to find a processed image such that it minimizes mean square error MSE, MAE and increases the value of the PSNR.

We have done simulations with uniform random noise added to the MR image. An example of a noisy magnetic resonance image (MRI) which consists of 256X256 pixels is shown in Fig. 3. As can be seen in the background the image has been uniformly corrupted with additive noise. The de-noising techniques discussed in the previous section are applied to the noisy MR image to test the efficiency of the different threshold methods.

For comparison of the five different wavelet functions, the quantitative de-noising results of the MRI images obtained by using global thresholding are shown in Table I and II respectively. The MSE, MAE, PSNR error criteria are the ones which have been used to assess the performance of the wavelet functions. Their numerical results are summarized in the tables.

Table 1: Qualitative analysis (MRI image) –Global Thresholding at Level-1

<table>
<thead>
<tr>
<th>TYPE OF WAVELET</th>
<th>LEVEL 1</th>
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<tbody>
<tr>
<td></td>
<td>PSNR</td>
<td>MSE</td>
<td>MAE</td>
</tr>
<tr>
<td>Haar</td>
<td>24.7316</td>
<td>0.0049</td>
<td>0.0049</td>
</tr>
<tr>
<td>db2</td>
<td>24.4483</td>
<td>0.0052</td>
<td>0.0442</td>
</tr>
<tr>
<td>db4</td>
<td>24.1475</td>
<td>0.0056</td>
<td>0.0448</td>
</tr>
<tr>
<td>sym2</td>
<td>24.4483</td>
<td>0.0052</td>
<td>0.0442</td>
</tr>
<tr>
<td>sym4</td>
<td>24.4292</td>
<td>0.0053</td>
<td>0.0444</td>
</tr>
<tr>
<td>bior1.1</td>
<td>24.2885</td>
<td>0.0054</td>
<td>0.0449</td>
</tr>
<tr>
<td>bior 1.3</td>
<td>24.6303</td>
<td>0.0050</td>
<td>0.0435</td>
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Table 2: Qualitative analysis (MRI image) – Global Thresholding at Level-2

<table>
<thead>
<tr>
<th>TYPE OF WAVELET</th>
<th>LEVEL 2</th>
<th>PSNR</th>
<th>MSE</th>
<th>MAE</th>
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<tr>
<td>Haar</td>
<td>23.0408</td>
<td>0.0072</td>
<td>0.0523</td>
<td></td>
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<tr>
<td>db2</td>
<td>22.8390</td>
<td>0.0076</td>
<td>0.0526</td>
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<tr>
<td>db4</td>
<td>22.5817</td>
<td>0.0080</td>
<td>0.0530</td>
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</tr>
<tr>
<td>sym2</td>
<td>22.8390</td>
<td>0.0076</td>
<td>0.0526</td>
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<td>22.8669</td>
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<td>bior1.1</td>
<td>22.7250</td>
<td>0.0078</td>
<td>0.0525</td>
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<tr>
<td>bior 1.3</td>
<td>22.9785</td>
<td>0.0073</td>
<td>0.0529</td>
<td></td>
</tr>
</tbody>
</table>

- It is clear from the table I & II, for Global thresholding technique; haar(db1) gives best result for level1 & level2.
- From the comparison results it can be observed, that the haar(db1) wavelet & global thresholding technique gives greatly improved de-noising results for both level-1 & level-2.
- Hence from the above tables, we observed that for both Simulated & MRI Image, haar(db1) Wavelet & Global Thresholding technique gives the best denoised results. Its gives higher PSNR & lower MSE & MAE value.

VII. CONCLUSION

The de-noising process consists of decomposing the image, thresholding the detail coefficients, and reconstructing the image. The decomposition procedure of the de-noising example is accomplished by using the DWT. Wavelet thresholding is an effective way of de-noising as shown by the experimental results obtained with the use of different types of wavelets. Thresholding methods implemented comprised of the global thresholding. More levels of decomposition can be performed; the more the levels chosen to decompose an image, the more detail coefficients we get. But for denoising the noisy MR data sets, two-level decomposition provided sufficient noise reduction.

In this paper we have presented the generalization of the DWT method for the 2-D case. The resulting algorithms have been used for the processing of noisy MR image. Experimental results have
shown that despite the simplicity of the proposed de-noised algorithm it yields significantly better results both in terms of visual quality and mean square error values. Considering the simplicity of the proposed method, we believe these results are very encouraging for other forms of de-noising. The haar wavelet (db1) gave the best results compared to other wavelets for both Simulated & MRI image respectively. The db4 wavelet has the poorest performance with the least PSNR and the highest MSE.

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