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A MODIFIED ALGORITHM FOR DENOISING MRI IMAGES OF LUNGS USING DISCRETE WAVELET TRANSFORM

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ABSTRACT
Image de-noising has become an essential exercise in medical imaging especially the Magnetic Resonance Imaging (MRI). The classical problem in the field of biomedical signal or image processing is the de-noising of image naturally corrupted by noise. Additive random noise can easily be removed using simple threshold methods. This paper proposes a medical image denoising algorithm using Discrete Wavelet Transform (DWT). Numerical results show that the algorithm can obtained higher peak signal to noise ratio (PSNR) through wavelet based denoising algorithm for MR images corrupted with random noise.

INDEX TERM
Biomedical Image Processing, De-noising, DWT, MRI, Thresholding, Random Noise. PSNR, MAE (mean absolute error) and MSE(mean square error).

1. INTRODUCTION
Image denoising is a procedure in digital image processing aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality. Medical images obtained from MRI are the most common tool for diagnosis in Medical field. These images are often affected by random noise arising in the image acquisition process. The presence of noise not only produces undesirable visual quality but also lowers the visibility of low contrast objects. Noise removal is essential in medical imaging applications in order to enhance and recover fine details that may be hidden in the data.

MR images are typically corrupted with noise, which hinder the medical diagnosis based on these images. The process of noise suppression must not appreciably degrade the useful features in an image. In particular, edges are important features for MR images and thus the denoising must be balanced with edge preservation.

Wavelets are popular for such image denoising and enhancement applications because they have good localization properties both in space and frequency. Further, use of wavelet packets allows adaptive representation for a given signal. A brief survey of representative techniques for image denoising is now presented. Lee and Tsai discuss the use of wavelets for image enhancement in [5]. Zadeh et al compare various filters (ratio, log ratio and angle image filters) to enhance MR images in [15]. In [7], the authors have looked at noise suppression in MR images using Fourier spectral methods. In [16], the authors used FIR filters along with wavelet decomposition for image enhancement, specifically edge enhancement and edge detection. Recently, in [5] the authors have used wavelets to enhance MR images. They used a mapping function to manipulate the transform coefficients before reconstruction. The mapping function was chosen such that the low frequency coefficients are notaffected which prevents distortion. The coefficients with larger absolute values contain more information while the high frequency coefficients contain important edge information. Hence, coefficients belonging to either of these classes were heavily weighted compared to other coefficients. In [13], the author discusses the use of soft-thresholding for image denoising. More recently, denoising using MDL based thresholding was introduced in [8].

From the above review of research papers, it is quite clear that wavelet has provided a very handsome amount of contribution in image denoising. A good number of aforesaid methods have been applied to different type of images. But among these papers, we found that one of the techniques, custom thresholding using wavelets, was developed only for signals (one dimensional) and has not been applied to two dimensional problems like for example images. Hence, we modified and proposed the same technique for images.

2. THE DISCRETE WAVELET TRANSFORM
The transform of a signal is just another form of representing the signal. It does not change the information content present in the signal. The Wavelet Transform provides a time-frequency representation of the signal. It was developed to overcome the short coming of the Short Time Fourier Transform (STFT), which can also be used to analyze non-stationary signals. While STFT gives a constant resolution at all frequencies, the Wavelet Transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions [3].

A wave is an oscillating function of time or space and is periodic. In contrast, wavelets are localized waves. They have their energy concentrated in time or space and are suited to analysis of transient signals. While Fourier Transform and STFT use waves to analyze signals, the Wavelet Transform uses wavelets of finite energy.

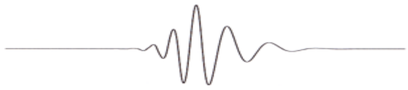

Figure 1 Demonstration of a Wavelet

3. METHODOLOGY

De-noising 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 algorithm used is explained below in the following steps:

Algorithm 1: Image de-noising

- 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.
- Estimation of a threshold
- Choice of a shrinkage rule[9] and application of the threshold to the detail coefficients. This can be accomplished by hard (Eq. (1)) or soft thresholding (Eq. (2)
- Application of the inverse transform (wavelet reconstruction) using the modified (threshold) coefficients.

4. THRESHOLDING

Thresholding is a technique used for signal and image de-noising. The shrinkage rule defines how we apply the threshold [10]. There are two main approaches which are:

I. Hard thresholding [4] deletes all coefficients that are smaller than the threshold λ and keeps the others unchanged. The hard thresholding is defined as follows:

$$\bar{c}_h(k) = \begin{cases} \text{sign } c(k)\ (|c(k)|) & \text{if } |c(k)| > \lambda \\ 0 & \text{if } |c(k)| \leq \lambda \end{cases} \quad (1)$$

Where λ is the threshold and the coefficients that are above the threshold are the only ones to be considered. The coefficients whose absolute values are lower than the thresholds are set to zero.

II. Soft thresholding deletes the coefficients under the threshold, but scales the ones that are left. The general soft shrinkage rule is defined by:

$$\bar{c}_s(k) = \begin{cases} \text{sign } c(k)\ (|c(k)| - \lambda) & \text{if } |c(k)| > \lambda \\ 0 & \text{if } |c(k)| \leq \lambda \end{cases} \quad (2)$$

4.1 Global Threshold

The global threshold method derived by Donoho is given by Eq. (4.3) has a universal threshold [2]:

$$\lambda = \sigma\sqrt{2\log(N)} \quad (3)$$

Where N is the size of the coefficient arrays and σ2 is the noise variance of the signal samples.

4.2 Level Dependent Threshold

Level dependent thresholding method is done by using Eq. (4). Estimation of the noise standard deviation σ_k is done by using the robust median estimator in the highest sub-band of the wavelet transform

$$\lambda_k = \sigma_k\sqrt{2\log(N)} \quad (4)$$

Where the scaled MAD noise estimator computed by:

$$\sigma_k = \frac{MAD_k}{0.6745} = \frac{(median(|\omega_i|))_k}{0.6745} \quad (5)$$

Where MAD is the median absolute deviation of the magnitudes of all the coefficients at the finest decomposition scale and ω_i are the coefficients for each given sub-band, the factor 0.6745 in the denominator rescales the numerator so that σ_k is also a suitable estimator. The threshold estimation method is repeated for each sub-band separately, because the sub-bands exhibit significantly different characteristics.

4.3 Optimal Threshold Estimation

Estimate the mean square error function to that compute the error of the output to minimize the function, the minimum MSE serves as a solution to the optimal threshold.

A function of the threshold value which is minimized is defined in Eq. (6).

$$G(\lambda) = MSE(\lambda) = \frac{1}{N}||y - y_\lambda||^2 \quad (6)$$

If y_λ is the output of the threshold algorithm with a threshold value λ and y is the vector of the clean signal, the remaining noise on this result equals $e_\lambda = y_\lambda - y$.

5. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

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

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

Algorithm Implementation

We used MATLAB to implement the de-noising algorithm. MATLAB has a wavelet toolbox and functions which are very convenient to do the DWT. A usual way to de-noise is to find a processed image such that it minimizes mean square error MSE and increases the value of the PSNR.

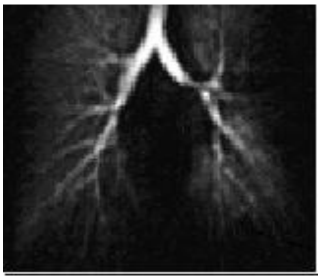

Figure 2-Original Image

Figure 3:-Noisy Image

For comparison of the five different wavelet functions, the quantitative de-noising results of the MRI images obtained by using global, level-dependent and optimal thresholding are shown in Table 1, 2 and 3 respectively. The MSE, 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 Quality Analysis (MRI Image) - Global Thresholding

Type of wavelet	LEVEL 1		
	MSE	**MAE**	**PSNR(db)**
Haar	0.0097	0.0771	22.400
db4	**0.0088**	**0.0740**	**22.6872**
sym2	0.0093	0.0748	22.6695
sym4	0.0097	0.0762	22.3020
sym8	0.0098	0.0766	22.1877
bior1.1	0.0097	0.0767	22.6442
bior 1.3	0.0099	0.0777	22.5340

Table 2 Quality Analysis (MRI Image) - Level Dependent Thresholding

Type of wavelet	LEVEL 1		
	MSE	**MAE**	**PSNR(db)**
Haar	0.0099	0.0775	22.1475
db4	0.0090	0.0743	22.6176
sym2	**0.0085**	**0.0732**	**22.6655**
sym4	0.0098	0.0765	22.2485
sym8	0.0099	0.0767	22.1533
bior1.1	0.0098	0.0769	22.5927
bior 1.3	0.0101	0.0783	22.4240

Table 3 Quality Analysis (MRI Image) - Optimal Thresholding

Type of wavelet	LEVEL 1		
	MSE	**MAE**	**PSNR(db)**
Haar	0.0072	0.0684	23.5469
db4	0.0072	0.0682	23.5750
sym2	0.0072	0.0684	23.7537
sym4	0.0071	0.0677	23.6506
sym8	0.0069	0.0664	23.7860
bior1.1	0.0071	0.0681	23.9652
bior 1.3	**0.0070**	**0.0664**	**24.0557**

Hence from the above tables, we observed that for MRI lungs Image, **bior1.3 wavelet and Optimal Thresholding** technique gives the best denoised results. Its gives higher PSNR, lower MSE and MAE value.

6. CONCLUSION

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 Biorthogonal wavelet (bior1.3) gave the best results compared to other wavelets for MRI image respectively. Optimal thresholding gives better denoised result among the three thresholding technique.

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