Noise Reduction in MRI Liver Image Using Discrete Wavelet Transform

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Abstract - *Image denoising is still a greatest challenge for researchers in digital image processing. The principal source of noise in digital images arise during image acquisition and/or transmission. The main property of a good image denoising model is that it will remove noise and preserve edges. The medical images are usually corrupted by noise which may lead to false diagnosis and treatment of disease. So image denoising has become an important pre-processing step in medial image analysis. In this work an MRI liver image is taken as an input image and noise is added to the image and denoised by mean and median filters by applying DWT. Wavelet transform is used to remove noise effectively and improves the quality of the image. Finally we analyse the performance of the denoised medical image to find the better result. The performance of the denoised medical image is calculated by Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), and Accuracy (ACC).*

Key Words: **Image denoising, DWT(Discrete Wavelet Transform), PSNR, MSE, ACCURACY.**

1.INTRODUCTION:

Image denoising is an important pre-processing task in digital image processing. All digital images have noise from different sources. Noise disturbances may be caused during image acquisition and/or transmission. The main property of a good image denoising model is that it should remove noise and maintain the quality. Noise Reduction is the most important step in medical field. Medical imaging is the technique that creates visual representations of the interior of the body in order to diagnose, monitor or treat medical conditions. MRI is one of the most common tool used in medical field for diagnosis. Mostly all medical images contain high level components of noise which leads to false diagnosis and treatment of disease. Noise is a random variation of brightness or color information in images which degrades the image quality. Noises may be additive, multiplicative. Additive noise is Gaussian noise, multiplicative noise is Speckle noise. Medical images are mostly corrupted by multiplicative noise. To achieve noise reduction goal some transforms are used. Discrete Wavelet Transform is a powerful tool for noise reduction and it decompose the image into high and low frequency sub-bands, which consists of half the number of signal of the original image. In this paper noise is added to the image and image is denoised using mean and median filters by applying Discrete Wavelet Transform (DWT).

2. RELATED WORKS:

The importance of denoising algorithm is to completely remove noise as far as possible and preserve edges. There are two models linear and non linear. Generally linear models are used. The benefit of linear noise removal model is speed and drawback is they do not preserve edges in an image. Non-linear model can handle edges in a better way. The most popular non-linear image de-noising is Total Variation (TV) filter. The performance of Wiener filter after de-noising for all Speckle, Poisson and Gaussian noise is better than mean filter and median filter. The performance of the median filter after de-noising for all Salt & Pepper noise is better than Mean filter and Wiener filter[1]. Three different wavelets Haar, Db2 & Sym4 with hard & soft thresholding have been analysed. Sym4 wavelet is most efficient among all three for removing the gaussian noise with different variance in the medical images and also it enhances the visual quality of the medical images[2]. When light is thrown on some type of noise and comparative analysis of noise removal technique show that BM3D and median filters perform well, and averaging and median filters perform worst. BM3D is the best of removing Salt & Pepper noise whereas in other cases median filter is more suitable[3].

Image de-noising using discrete wavelet transform is analyzed and experiments were conducted to study the suitability of different wavelet bases and also different window sizes. Among all discrete wavelet bases, coiflet performs well in image denoising. Experimental results show that modified Neighshrink gives better results than Neighshrink, Wiener filter and Visushrink[4]. Denoising of different medical images like MRI, Ultrasound, X-ray, CT is performed using haar and db3 wavelets at both soft and hard threshold levels and PSNR value is calculated and it is found that db3 wavelet is more efficient than haar for removing certain level of speckle noise in the medical images and also it enhances the visual quality of the medical images[5]. Two main issues regarding image denoising were addressed in this paper. Firstly, an adaptive threshold for wavelet thresholding images was proposed, based on the GGD modeling of subband coefficients, and test results showed excellent performance. Secondly, a coder was designed specifically for simultaneous compression and denoising. The proposed BayesShrink threshold specifies the zero-zone of the quantization step of this coder, and this zero-zone is the main agent in the coder which removes the noise[6].

An improved method of NeighShrink (proposed method) using the Stein's unbiased risk estimate (SURE) by using optimal threshold and neighbouring window size for every wavelet subband instead of using the suboptimal universal threshold and same neighbouring window size in all subbands. Experimental results conclude that NeighShrink produce good results compare to VisuShrink and SureShrink[7]. Impulse noise removal for gray scale images using the standard median filter and its variants are analysed. Results show that tristate median filter and switching median filter exhibit visually appealing results. The other methods such as standard median filter, adaptive median filter, weighted median filter lack in preserving edges while retaining some noise components[8].

A new technique formed by the hybridizing the thresholding technique of the image decomposed using discrete wavelet transform along with the transformation of intensity to obtain a noise free, high quality denoised image[9]. To examine various algorithms and discrete wavelet transform and understanding the concept of denoising[10]. Salt and Pepper noise removal from various types of compound images using median filter. Performance analysis show that median filter give better results for compound document images compared with scanned compound images[11].

3. MOTIVATION AND JUSTIFICATION:

Denoising is the process of removing noise from the image and preserve all the relevant features of the image. There are numerous techniques available for denoising purpose. The selection of denoisng technique depends on the type of image and the noise present in the image.

Our aim in this paper is to remove noise from an MRI liver image. Denoising improves the quality of the image so decomposition and noise removal filters are uesd. For decomposing the image we use DWT and for removing the noise we use mean and median filters. Then we reconstruct the image by using inverse DWT. The image quality measures help in the detection of the quality of the image. We calculate PSNR (Peak Signal to Noise Ratio), MSE (Mean Squrare Error) and ACC (Accuracy) values and compare the results.

4. ORGANISATION OF THE PAPER:

The paper is organized as follows: Section 5 includes Methodology which includes outline of the proposed work, Section 6 includes Experimental Results, Section 7 includes Performance Evaluation and Section 8 includes Conclusion of the paper.

5. METHODOLOGY:

OUTLINE OF THE PROPOSED METHOD:

We take an MRI liver image as an input image and add noises namely gaussian noise, salt and pepper noise, and speckle noise with different noise variance ranging from (0.01-0.08). The input image is transformed in to 2D DWT and the image is decomposed into 4 sub-bands namely LL, LH, HL, HH using different wavelets iteratively using Biorthogonal, Coiflet, and Symlet. The decomposed image is denoised using mean and median filters. Then we reconstruct the denoised image by using the inverse wavelet transform. The performance quality is measured by metrics PSNR, MSE and Accuracy and then the results are compared.

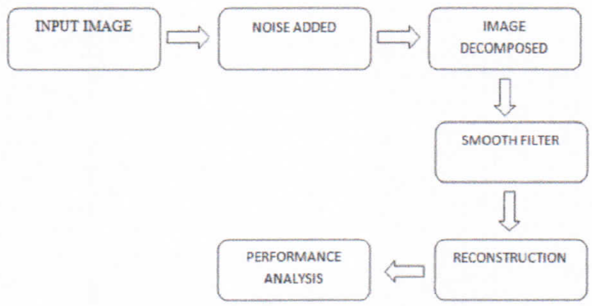

Fig 1.Flowchart of the methodology.

NOISE MODELS:

GAUSSIAN NOISE OR NORMAL NOISE:

Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. The principal source of Gaussian noise in digital image arise during image acquisition. It exists due to factors such as electronic circuit noise and sensor noise due to poor illumination and/or high temperature. The PDF of gaussian noise is given by

$$p(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(z-\bar{z})^2/2\sigma^2}$$

SALT AND PEPPER (IMPULSE) NOISE:

Salt-and-pepper noise is a form of noise sometimes seen on images. It presents itself as sparsely occurring white and black pixels. The PDF of salt and pepper noise is given by

$$p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases}$$

$$P_a = P_b \Rightarrow \textit{unipolar} \text{ noise}$$

SPECKLE NOISE:

Speckle is a granular 'noise' that inherently exists in and degrades the quality of the active radar, synthetic aperture radar (SAR), medical ultrasound and optical coherence tomography images. The PDF of speckle noise is given by

$$F(g) = \frac{g^{\alpha-1} e^{\frac{-g}{a}}}{\alpha - 1! a^{\alpha}}$$

DISCRETE WAVELET TRANSFORM:

Discrete wavelet transform (DWT) uses the scale parameter as well as the shifting parameter for wavelet transformation. The scale parameter either expands or compresses the width of a wavelet function while maintaining its basic structure. The larger a scale value becomes, the greater the width becomes, presenting the features of a low-frequency component. In contrast, the smaller a scale value becomes, the greater the features of a high-frequency component. The shifting parameter determines the position of functions along the time axis. As the value of shifting parameters become larger, the functions move to the right in parallel.

The discrete wavelet transform is used for image noise removal. It will perform the sub band decomposition. This decomposition is done by row and column wise processing the image. Wavelet splits the image into 4 sub bands such as LL, LH, HL, HH. The LL image contains the low frequency components while LH, HL and HH contains high frequency components in horizontal, vertical and diagonal directions respectively. Approximation part is LL, and the other part is detailed part. The sub-band LL which is the approximation of digital image is further decomposed by discrete wavelet transform to get any level of decomposition of the digital content and it will generate the further four sub-bands. Thus the information of image is stored in decomposed form in these sub-bands.

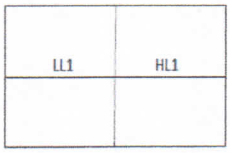

Fig.2 Decomposition of image at Level 1

WAVELET FAMILIES:

SYMLET WAVELET:

Symlet wavelets are a family of wavelets which are nearly symmetrical wavelets proposed by Daubechies as modification to the db family. The properties of the two wavelet families are similar. There are 7 different symlet functions from sym2 to sym8. In symN, N is the order.

COIFLET WAVELET:

Coiflets are discrete wavelets which have scaling functions with vanishing moments. The wavelet is near symmetric, their wavelet functions has 2N moments equal to 0 and scaling functions has 2N-1 moments equal to 0. The two functions have a support of length 6N-1.

BIORTHOGONAL WAVELET:

A biorthogonal wavelet is a wavelet where the associated wavelet transform is invertible but not necessarily orthogonal. Designing biorthogonal wavelets allows more degrees of freedom than orthogonal wavelets. One additional degree of freedom is the possibility to construct symmetric wavelet functions.

In the biorthogonal case, there are two scaling functions $\varphi, \tilde{\varphi}$ which may generate different multiresolution analyses, and accordingly two different wavelet functions $\psi, \tilde{\psi}$. So the numbers M and N of coefficients in the scaling sequences $a, \tilde{a}$ may differ. The scaling sequences must satisfy the following biorthogonality condition

$$\sum_{n\in\mathbb{Z}} a_n \tilde{a}_{n+2m} = 2 \cdot \delta_{m,0}$$

Then the wavelet can be determined as

$$b_n = (-1)^n \tilde{a}_{M-1-n} \quad (n = 0, \ldots, N-1)$$
$$\tilde{b}_n = (-1)^n a_{M-1-n} \quad (n = 0, \ldots, N-1)$$

FILTERS:

Filtering is a technique for modifying or enhancing an image. we can filter an image to emphasize certain features or remove other features. Image processing operations implemented with filtering include smoothing, sharpening and edge enhancement.

Filtering is a neighborhood operation, in which the value of any given pixel in the output image is determined by applying some algorithm to the values of the pixel in the neighborhood of the corresponding input pixel. A pixel's neighborhood is some set of pixels, defined by their locations relative to that pixel.

MEAN FILTER:

The mean filter is a simple sliding-window spatial filter that replaces the center value in the window with the average (mean) of all the pixel values in the window. The window or kernel, is usually square but can be any shape. Center value is replaced by the mean values.

MEDIAN FILTERS:

The median filter is a nonlinear digital filtering technique, often used to remove noise. Median filtering is very widely used in digital image processing because under certain conditions, it preserves edges while removing noise. The median filter is also a sliding-window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window.

6. EXPERIMENTAL RESULTS:

Experiments were conducted to denoise an MRI liver image shown in Fig.3. To the original image Gaussian Noise, Salt & Pepper noise and speckle noise are added. Then the image is decomposed by using wavelet bases at level 1 and filters are applied and the results are given in Fig.4.

Fig.3 Input image

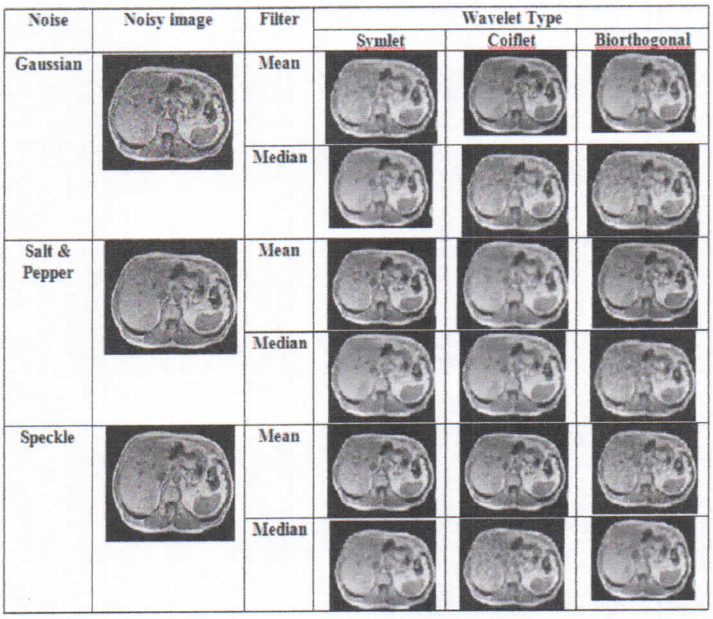

Fig 4. Wavelet bases for denoised image

PERFORMANCE METRICS:

MSE (MEAN SQUARED ERROR):

Mean Squared Error (MSE) is the average squared difference between input and denoised output image. The error is the amount by which the value obscure by the estimator differs from the quantity to be estimated. The image quality parameters used in this work for comparing the denoised result with the original image. It is expressed as

$$MSE = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} [f(x,y) - \hat{f}(x,y)]^2$$

PSNR (PEAK SIGNAL TO NOISE RATIO):

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

$$PSNR = 10 * \log_{10}\left(\frac{255^2}{MSE_{min}}\right)$$

ACCURACY:

Accuracy is the degree to which information in a digital databases matches true or accepted values. It is a measure close to the actual value. It is the proportion of true results.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

7. PERFORMANCE EVALUATION:

In evaluating the performance different wavelet bases and filtering techniques were presented. Performance is calculated by PSNR, MSE, and ACCURACY. In Table 1 different wavelet bases are presented, Gaussian noise for symlet with median filter perform well. By varying the noise levels, results are taken and shown in Table 2, and Table 3.

Table 1:Wavelet Bases vs Filter

Noise	Filter	PSNR			MSE			ACCURACY		
		SYM	COIF	BIOR	SYM	COIF	BIOR	SYM	COIF	BIOR
S&P	Mean	55.86714	54.36442	53.57081	0.186853	0.254232	0.290318	81.31467	74.57681	70.9682
	Median	55.13168	53.35303	52.74139	0.20511	0.308622	0.346338	79.489	69.13779	65.36624
Gaussian	Mean	59.0963	55.52011	53.6406	0.105284	0.206059	0.28823	89.4716	79.39408	71.17703
	Median	59.35303	55.72338	53.79016	0.090476	0.200364	0.274102	90.95238	79.96361	72.58978
Speckle	Mean	52.67029	52.1283	52.43908	0.351606	0.398339	0.370843	64.83942	60.16611	62.91568
	Median	52.89225	52.16067	52.42517	0.33414	0.39538	0.37203	66.58598	60.46195	62.79703

Table 2:Noise Variance vs Mean Filter

Noise variance	Salt & pepper noise for symlet with mean filter			Gaussian noise for symlet with mean filter			Speckle noise for symlet with mean filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	69.22955	0.307704	53.24947	75.69214	0.243079	54.27334	64.61794	0.353821	52.64297
0.02	74.60845	0.253916	54.08391	86.47366	0.135263	56.819	64.77614	0.352239	52.66243
0.04	83.70511	0.162949	56.01029	92.65939	0.073406	59.47348	64.95017	0.350498	52.68394
0.06	87.63645	0.123636	57.20937	95.7127	0.042873	61.80897	64.76823	0.352318	52.66146
0.08	91.39377	0.086062	58.78267	96.82012	0.031799	63.1067	65.08464	0.349154	52.70064
Noise variance	Salt & pepper noise for coifllet with mean filter			Gaussian noise for coiflet with mean filter			Speckle noise for coiflet with mean filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	62.276539	0.3772346	52.364688	62.9489	0.370511	52.442793	60.006328	0.3999367	52.110891
0.02	66.405632	0.3359437	52.868139	73.398196	0.266018	53.881693	60.13289	0.3986711	52.124656
0.04	76.649264	0.2335074	54.447798	82.170543	0.1782946	55.619422	60.227812	0.3977219	52.135009
0.06	81.545642	0.1845436	55.469814	88.166429	0.1183357	57.399646	60.393925	0.3960607	52.153186
0.08	86.006961	0.1399304	56.671683	90.286347	0.0971365	58.256978	60.069609	0.3993039	52.117768
Noise variance	Salt & pepper noise for biorthogonal with mean filter			Gaussian noise for biorthogonal with mean filter			Speckle noise for biorthogonal with mean filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	67.560513	0.3243949	53.020064	65.456415	0.3454358	52.74713	62.37937	0.3762063	52.376543
0.02	70.637557	0.2936244	53.452882	64.388546	0.3561145	52.614907	63.083373	0.3691663	52.458583
0.04	64.174972	0.3582503	52.588938	73.03433	0.2696567	53.822691	62.656225	0.3734377	52.408621
0.06	73.698782	0.2630122	53.931045	71.808258	0.2819174	53.629585	63.249486	0.3675051	52.478169
0.08	78.769182	0.2123082	54.861136	81.197595	0.188024	55.38867	63.209935	0.3679006	52.473498

Table 3: Noise Variance vs Median Filter

Noise variance	Salt & pepper noise for symlet with median filter			Gaussian noise for symlet with median filter			Speckle noise for symlet with median filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	74.14175	0.258583	54.00481	82.32875	0.176713	55.65813	66.16833	0.338317	52.83757
0.02	75.25708	0.247429	54.19629	87.50198	0.12498	57.16239	66.84069	0.331593	52.92475
0.04	78.24711	0.217529	54.75563	92.84132	0.071587	59.58248	65.64626	0.343537	52.77106
0.06	83.87913	0.161209	56.05692	95.64942	0.043506	61.74533	67.42604	0.32574	53.0021
0.08	85.91995	0.140801	56.64476	96.44044	0.035596	62.61684	66.8486	0.331514	52.92578
Noise variance	Salt & pepper noise for coiflet with median filter			Gaussian noise for coiflet with median filter			Speckle noise for coiflet with median filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	61.50925	0.384907	52.27724	66.09714	0.339029	52.82844	60.43348	0.395665	52.15752
0.02	63.24949	0.367505	52.47817	70.77994	0.292201	53.47399	60.47303	0.39527	52.16187
0.04	68.05094	0.319491	53.08622	83.28587	0.167141	55.89997	60.36228	0.396377	52.14972
0.06	72.78912	0.272109	53.78338	87.19348	0.128065	57.05649	60.3781	0.396219	52.15145
0.08	80.09018	0.199098	55.14013	92.46164	0.075384	59.35803	60.66287	0.393371	52.18278
Noise variance	Salt & pepper noise for biorthogonal with median filter			Gaussian noise for biorthogonal with median filter			Speckle noise for biorthogonal with median filter		
	ACC	MSE	PSNR	ACC	MSE	PSNR	ACC	MSE	PSNR
0.01	63.66081	0.363392	52.52705	66.37399	0.33626	52.86405	63.15456	0.368454	52.46697
0.02	63.92185	0.360782	52.55836	70.49517	0.295048	53.43187	62.98054	0.370195	52.4465
0.04	64.68122	0.353188	52.65075	74.22085	0.257791	54.01812	62.85398	0.37146	52.43168
0.06	66.23161	0.337684	52.8457	75.12261	0.248774	54.17275	62.26863	0.377314	52.36378
0.08	68.33571	0.316643	53.12511	76.73628	0.232637	54.46401	62.72742	0.372726	52.41691

8. CONCLUSIONS:

In this paper, three different wavelets symlet, coiflet, biorthogonal have been implemented for image denoising based on Discrete Wavelet Transform (DWT). DWT is a good tool for image denoising. Image qualitative are measured by PSNR, MSE and ACCURACY. In DWT, symlet performed well against all noises. We observe that for all three noises mean filter with symlet gives best results in ACCURACY.

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