Comparision And Analysis Of Wavelet Based Image Denoising Techniques

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Abstract— - **One of the primal tasks in the area of image processing and computer vision is denoising images. The medical image are made noisy through with white Gaussian noise with a particular noise variant. In this paper we compared various denoising methods of medical images through Wavelet based thresholding and optimization techniques.There have been several published methods and algorithms and each and every approach has its own advantages, limitations and assumptions. This paper presents a review of some significant work in the area of image denoising. In these algorithms, not only PSNR is increased ,but also the quality of picture and vision are improved. moreover its bigger along with the noise variance, the PSNR and quality of the pictures better.**

Index Terms—— ***Image Denoising; Thresholding; Gaussian Noise; Peak Signal To Noise Ratio(PSNR)***

I. INTRODUCTION

Medical images are corrupted by Gaussian white noise is a major problem in image processing. Wavelet denoising method has been a popular research work because wavelet de- noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform. The noise suppression method solved by this method are as follows: Let x(t) be a original image and y(t) be the image corrupted with identically distributed zero mean, z(t) be a white Gaussian noise.

$$y(t) = x(t) + \sigma_n z(t) \tag{1}$$

The methodology of the discrete wavelet transform(DWT) based image de-noising has the following three steps as 1. Transform the noisy image into orthogonal domain by 2D discrete wavelet transform. 2. Apply the threshold i.e hard or soft thresholding in the noisy detail coefficients of the wavelet transform 3. Inverse discrete wavelet transform (IDWT) is performed to obtain the de-noised image[1-3]. The contourlet and wavelet techniques with dual tree complex and real and double density wavelet transform denoising methods are performed to real ultrasound images and results were quantitatively compared[4][5]. Images denoised by TV, wavelet and AVREC methods. The proposed method is also compared with the total variation (TV) denoising and wavelet thresholding methods[6].In this paper, the multiresolution structure and sparsity of waveletsare employed by nonlocal dictionary learning in each decomposition level of the. wavelets[7] ,which shows the various methods of the wavelet. The proposed methods builds a nonlocal hierarchical sparse dictionary on the wavelet coefficients of a noisy image. The curvelet based methods yield better results for CT images and the TV method is suitable for MRI images. Total variation method and Curvelet transform mehod is also very effective for image denoising.we use two types of curvelet which are as follows: 1) curvelet denoising using hard thresholding 2) curvelet denoising using cycle spinning[8-12]. NL –means (NLM) algorithm and Median non -local means filtering (MNLM) i)The proposed method incorporates a median filtering operation indirectly in the nonlocal means (LM) method, which gives more robust estimation of the weights used to average the pixels in the medical images[13]. The neighboring wavelet thresholding idea was extended by Chen and Bui [14] in to the multi wavelet scheme. In this method it was proved that neighbor multi wavelet denoising outperforms the neighbor single wavelet denoising [15]. Neelamani has proposed the ForWardD[16] method in which they obtains suppression the noises in the images efficiently. Many noise removal techniques proposed by Mandal and Mukhopadhyay termed as ANDWP[17], EPRRVIN[18], GADI[19] and EKSI[20]. These filters perform excellent when applied to images corrupted with high, medium and low densities of noises.

The remainder of this paper is organized as follows: Section 2 describes the wavelet thresholding. Section 3 describes the problem statement of the research fields. Section 4 includes denoising algorithoms. Section 5 shows the results of experiments . Finally, conclusions and discussions are summarized this paper in section 6

II. WAVELET THRESHOLDING

Thresholding operation is done on wavelet transformed coefficients of the noisy image for noise suppression. Various methods have been introduced on thresholding the wavelet coefficients [21-25]. The wavelet shrinkage has commonly follow the following steps:

Manuscript received March, 2015
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ISSN: 2278 – 1323

1.Transform the noisy image by using forward discrete wavelet transform(DWT)
2. Estimate the threshold value.
3.the value of the threshold is apply on the wavelet coefficients according to a method of shrinkage.
4. Perform inverse discrete wavelet transform(IDWT) to achieve the de-noised image.

.Supoose $f = \{f_{ij}$, i, j = 1,2…N} denote the M·M matrix of the original image to be recovered and N is some integer power of 2.In between transmission the signal f is corrupted by independent and identically distributed (i.i.d) zero mean, white Gaussian Noise n_{ij}. The discrete wavelet transformation decomposes the noisy image into different frequency sub bands (LL, LH, HL and HH). labeled as *LLj*, *LHk*, *HLk* and *HHk*, where k=1,2,...,j. The implementation of 2D discrete wavelet decomposition is shown in Fig.1.

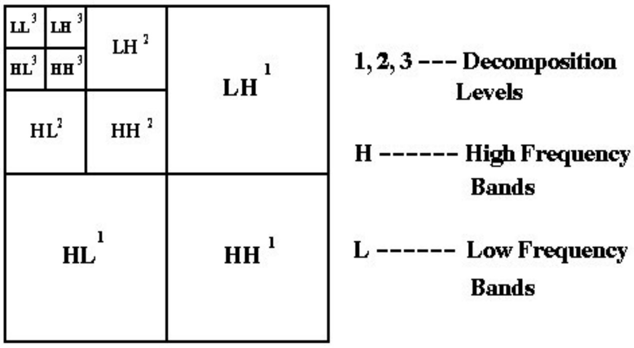


Fig. 1: 2D-DWT sub-image representation of wavelet with three level decomposition.

There exist following methods of estimating the thresholds in image de-noising based on wavelet transform. VisuShrink[26], SureShrink[27] , NormalShrink[28], BayesShrink[29-30]. These are presented as follows:

Method 1:VisuShrink
VisuShrink is a universal thresholding method where a single threshold is applied on level other wavelet coefficients entirely which is defined in eqn.

$$\lambda=\sqrt{2\log N} \tag{3}$$

This method executes well in a number of applications because wavelet transform has the compaction property of having only a small number of large coefficients.

Method 2: SureShrink
SUREShrink is a sub band adaptive thresholding scheme where a different threshold is estimated and applied for each sub band based on Stein's unbiased risk estimator (SURE). The function is given in eqn. 4

$$\lambda = \arg\min SURE(n, X) \tag{4}$$

Because the method is to order the wavelet coefficients in terms of magnitude and to select the threshold as the wavelet coefficient that minimizes the risk. As pointed out by Donoho, when the coefficients are not sparse, this thresholding method is applied.

Method 3: NormalShrink
This segment describes the method for calculating the various parameters used to calculate the threshold value (TN), which is adaptive to different subband characteristics.

$$T_n = \frac{\beta\sigma^2}{\sigma_y} \tag{5}$$

Method 4: BayesShrink
BayesShrink is a sub band adaptive data driven thresholding method. This method assumes that the wavelet coefficients are distributed as a generalized Gaussian distribution in each sub band. It also finds a threshold which minimizes the Bayesian risk.

$$\frac{\sigma_{noise}^2}{\sigma_{signal}} = \frac{\sigma_{noise}^2}{\sqrt{\max(\sigma_y^2-\sigma_{noise}^2, 0)}} \tag{6}$$

III. PROBLEM STATEMENT

Image denoising is an important task of image processing , for both as a process itself, and as a component in many other processes. Many ways to remove noise from an image or a set of data exists.Image denoising still remains a big challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper defines wavelet based denoising techniques for noise reduction (or denoising) giving an insight as to the different algorithms that should be find the most reliable estimate the threshold value of the original image data given its reduced version. Noise modeling in images is greatly affected by capturing the instruments, data transmission mode, image quantization and sources of radiation in discrete form. Different methods and algorithms are used depending on the noise model. Most of the original images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise [2] is observed in ultrasound images whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal technique for images.

IV. IMAGE DENOISING ALGORITHM

This segment describes the image denoising algorithms, which obtained the near optimal soft threshholding in the wavelet Domain for recovering original signal from the noisy one.

A. Genetic Algorithm(GA)

The GA based denoising starts with encoding randomly in initial populations. GA starts the encoding with population of having n numbers of chromosomes. The binary chromosome is converted to decimal and the threshold and decomposition level is take out. The threshold is added with the Bayesian threshold. Based on it the fitness is calculated using the new threshold and decomposition level to define each chromosome. Until an optimal solution obtained go through the selection, crossover and mutation stages. These stages are repeated to go the next generation. After a number of generations the best threshold value and the corresponding decomposition level is obtained. Using those two values the noisy image is restored and PSNR (dB) is calculated.In this algorithm various threshoding techniques

ISSN: 2278 – 1323

are implemented to obtain the most optimal threshold value.GA based shrinking methods are compared with the some existing filters to remove the Gaussian noise.

A. Particle Swarm Optimization Algorithm(PSO)

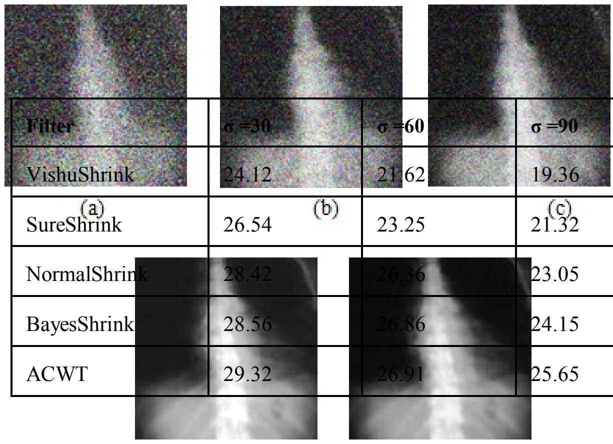
PSO are population based optimization algorithms modeled after the simulation of social behavior of birds form a flock.PSO is represents with a group of randomize solutions or particles and then searches for optima by updating generations. Each particle is flown through the search space, having its position adjusted based on its distance from its own personal best position and the distance from the best particle of the swarm. The performance of each particle, i.e how close the particle is from the global optimal solution, is evaluated by a fitness function to be optimized.

A. NL- Means Algorithm

The local smoothing methods and the frequency domain filters aim at a noise reduction and at a reconstruction of the main geometrical configurations but not at the preservation of the fine structure, details, and texture. Due to the regularity assumptions on the original image of previous methods, details and fine structures are smoothed out because they behave in all functional aspects as noise. The NL-means algorithm we shall now discuss tries to take advantage of the high degree of redundancy with any natural image. So, we simply understand that each and every small window in a natural image has many similar windows in the same image.

V. EXPERIMENTAL RESULTS

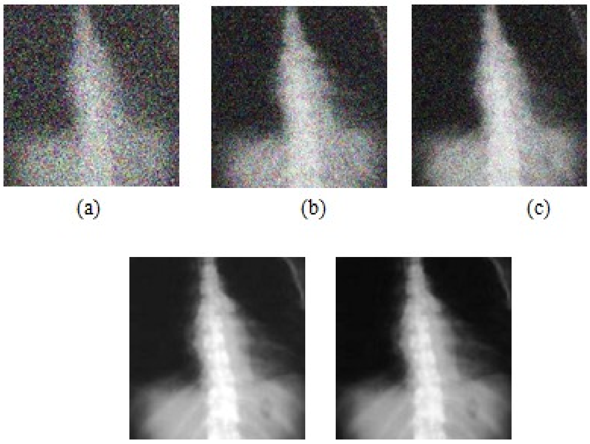
To benchmark against the best possible performance of a threshold estimate, the comparison is done among the existing methods. The best soft thresholding estimate obtainable assuming the original image known. The PSNR from various methods are compared in Table I and the data are collected from an average of the total five runs. So the main comparison is done in between the *SureShrink* and *BayesShrink*, the better one among these. *NormalShrink* outperforms *SureShrink* and *BayesShrink* most of the time in terms of PSNR as well as in terms of visual quality.The choice of soft thresholding over hard thresholding is justified from the results of best possible performance of a hard threshold estimator, *OracleThresh*. Fig.2 shows visual restoration results by applying the algorithms on the Ultrasound image corrupted with low,medium and high densities of Gaussian noises.thus these methods are not enough to preserve the image fine details and textures when the images have high density of Gaussian noises. The VisuShrink,Sureshrink and BayesShrink methods cannot suppress the noises in the images efficiently.thus we observe PSNR status of all those thresholding estimation methods and find the most suitable methods which is used along with the proposed algorithm.For the above mentioned four methods, image de-noising is performed using wavelets from the second level to fourth level decomposition and the results are shown in figure (2) and table if formulated for second leveldecomposition for different noise.In this figure(2) we show noisy ultrasound image and we try to restored the images by using Visushrink, SureShrink, NormalShrink,



(a) (b) (c)

(d) (e)

Filter	σ =30	σ =60	σ =90
VishuShrink	24.12	21.62	19.36
SureShrink	26.54	23.25	21.32
NormalShrink	28.42	26.36	23.05
BayesShrink	28.56	26.86	24.15
ACWT	29.32	26.91	25.65



(a) (b) (c)

(d) (e)

Fig:2 Restored images by Visushrink, SureShrink, NormalShrink, BayesShrink, ACWT respectively.

VI. CONCLUSION

Image Denoising; Thresholding, Gaussian Noise,Peak Signal To Noise Ratio(PSNR). Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. Many of the current techniques or methods assume that the noise model to be made noisy through the Gaussian noise.

But in reality, this assumptions are may not always to be true due to the different nature and the sources of noise, where they exist. An ideal procedure of denoising requires a priori knowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model. Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. Gaussian Noise with different variance values is added in the natural images to test the performance of the algorithm. When using Wavelet emphasized that issue such as choice of primary resolution (the scale level at which to begin thresholding) and choice of analyzing wavelet also have large influence on the success of the shrinkage procedure, This paper proposed a denoising algorithm for the

ISSN: 2278 – 1323

medical images which are corrupted with additive white Gaussian noise. In wavelet based image denoising thresholding method is applied which is estimated based on either the whole image or based on each sub band of the image. The image de-noising using discrete wavelet transform is analyzed. The experiments were conducted to study the suitability of different wavelet bases and also different window sizes.

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ISSN: 2278 – 1323