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Adaptive Threshoding for Wavelet Denoising on Medical Images through PSO Algorithm

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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 is made noisy through white Gaussian noise with a particular noise variance. In this thesis proposed a denoising method of medical images through thresholding and optimization using a randomized and stochastic technique of Particle Swarm Optimization(PSO) algorithm. PSO are population based optimization algorithm ,which is initialized with a group of random particles and then searches for optima by updating generations. This paper proposes an adaptive threshold estimation method for image denoising in the wavelet domain called as Bayes Shrink which is a sub band adaptive data driven thresholding method. In proposed algorithm, not only PSNR is enhanced ,but also the picture quality and vision are improved. moreover it bigger along with the noise variance, the PSNR and image quality is better. In this we compared various denoising methods of medical images through Wavelet based thresholding and optimization techniques. There have been several published algorithms and each approach has its assumptions, advantages, and limitations.**

Index Terms— ***Image Denoising; Thresholding; Gaussian Noise;Particle Swarm Optimization(PSO);Peak Signal to Noise Ratio (PSNR).***

I. INTRODUCTION

The image de-noising naturally corrupted by noise is a classical problem in the field of signal orimage processing. Additive random noise can easily be removed using simple threshold methods. De-noising of natural images corrupted by Gaussian noise using wavelet techniques are very effective because of its ability to capture the energy of a signal in few energy transform values. The wavelet de-noising scheme thresholds the wavelet coefficients arising from the standard discrete wavelet transform. In this paper, it is proposed to investigate the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR. Removing unwanted noise in order to restore the original image. One of the fundamental challenges in the field of image processing and computer vision is image denoising, where the underlying goal is to estimate the original image by suppressing noise from a noise-contaminated version of the image. Image denoising is an important image processing task, both as a process itself, and as a component in other processes.

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Very many ways to denoise an image or a set of data exists. The main properties of a good image denoising model is that it will remove noise while preserving edge. There are many types of noises occurs in medical images. Mostly occurred noise are Gaussian noise, Speckle noise, Salt and pepper noise, rician noise and Brownian noise etc. There rician noise corrupts the MRI images. Speckle noise corrupt the ultrasound images. When electron generated thermally at sensor site, dark current noise introduced in image. its sensor temperature dependent .

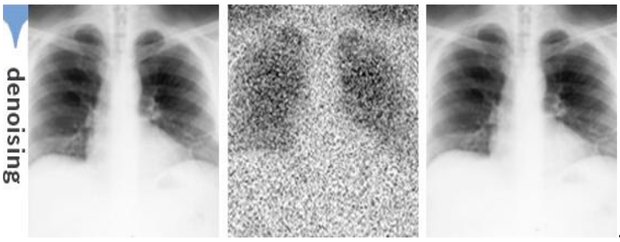


Figure 1.1 : Medical image denoising

Wavelet thresholding is a popular approach for denoising due to its simplicity.In its most basic form, this technique operates in the orthogonal wavelet domain, where each coefficient is thresholded by comparing against a threshold; if the coefficient is smaller than the threshold it is set to zero, otherwise, it is kept or modified. Wavelet thresholding is a popular approach for denoising due to its simplicity. In its most basic form, this technique operates in the orthogonalwavelet domain, where each coefficient is thresholded by comparing against a threshold; if the coefficient is smaller than the threshold it is set to zero, otherwise, it is kept or modified. One of the first reports about this approach was by Weaver et al [1]. A systematic theory was developed mainly by Donoho and Johnstone [2]-[5]. They have shown that various wavelet thresholding schemes for denoising have near optimal propertiesin the minimax sense and perform well in simulation studies of one dimensional curve estimation.. Particle Swarm Optimization (PSO) was introduced in 1995 by social psychologist James Kennedy and professor and chairman of electrical and computer .engineering Russell C. Eberhart to simulate the natural swarming behavior of birds as they search for food [6].The test function used was f(x)= $\sqrt{(x_1-100)^2}+\sqrt{(x_2-100)^2}$ which has a minimum function value of zero at Cartesian coordinates (100, 100). 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. Mukhopadhyay S. And Mandal J. K. Proposed the adaptive thresholding through Genetic algorithm.[7].

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

II. LITERATURE REVIEW

In this chapter we study the various denoising methods ofmedical 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. In this section we presents a review of some significant work in the area of image denoising. In these algorithms, they are try to increased the PSNR ,but also some problems are arised with these algorithms. This section investigates the suitability of different wavelet bases and the size of different neighborhood on the performance of image de-noising algorithms in terms of PSNR.Chang S. G. And B. Yu et. al. observed these observations are consistent with the nature of adaptive processes which account for the local statistics and characteristics of the signal. In general, adaptive approaches have shown to be more effective than their global counterparts. In this section, one such simple level-dependent wavelet thresholding technique will be studied.[8]-[11]..Ruomei Y. Et. al. has proposed the multiresolution structure and sparsity of waveletsare employed by nonlocal dictionary learning in each decomposition level of the wavelets. The proposed methods builds a nonlocal hierarchical sparse dictionary on the wavelet coefficients of a noisy image[12]. Bhadauria H.S. has proposed the curvelet based methods yield better results for CT images and the TV method is suitable for MRI images.[13].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. Matteo M. el al has proposed NL –means (NLM) algorithm and Median non -local means filtering (MNLM) i) Chen and Bui has 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 image. The neighboring wavelet thresholding idea was extended [14] in to the multi wavelet scheme. In this method it was proved that neighbor multi wavelet denoising outperforms the neighbor single wavelet denoising .Neelamani R. et. al.has proposed the ForWardD method in which they obtains suppression the noises in the images efficiently[15]. Many noise removal techniques proposed by J. K. Mandal et al. termed as ANDW ,EPRRVIN,GADI and EKSI. These filters perform excellent when applied to images corrupted with high, medium and low densities of noises. [16]. The development of efficient and adaptive image restoration techniques that account for the local statistics has become a rather popular research field and has attracted many researchers from different backgrounds. Mukhopadhyay S. And Mandal J. K. Proposed the adaptive thresholding through Genetic algorithm.Research conferences as well as journal issues were dedicated to this subject, such as [17] An adaptive recursive two-dimensional filtering technique for removing Gaussian noise in images was proposed in [18]. The adaptation was performed with respect to three local image features; edges, spots, and flat regions. Detectors for classifying these three subregions of the images were developed. The proposed filter was shown to perform simultaneous noise suppression and edge enhancement. A recursive and adaptive Wiener filter was proposed by adersan. A Wiener filter which locally estimates the power spectrum at various regions in the image was developed.A qualitative comparison of edge-preserving smoothing techniques was studied in [19]. Locally adaptive techniques for edge-preserving smoothing were proposed and compared. In [20], a novel method to smooth a signal while preserving preserving discontinuities was presented. An extensive review of wavelet thresholding in image processing found by Jansen M. [21].This method was shown to be extremely attractive since edge detection can be performed after only a few iterations, and features extracted from the smoothed signal are correctly localized. In, a new nonlinear filter for noise smoothing was introduced. The novel feature of the proposed filter is that it attempts to distinguish between meaningful contours (edges) and noise, so that the image can be smoothed without loss of important details. Many other adaptive image restoration techniques were studied in. Particle Swarm Optimization (PSO) was introduced in 1995 by social psychologist James Kennedy and professor and chairman of electrical and computer engineering Russell C. Eberhart to simulate the natural swarming behavior of birds as they search for food [22]. The test function used was f(x)= Particle Swarm Optimization (PSO) was introduced in 1995 by social psychologist James Kennedy and professor and chairman of electrical and computer engineering Russell C. Eberhart to simulate the natural swarming behavior of birds as they search for food in,1995. The test function used was f(x)= $\sqrt{(x_1-100)^2}+\sqrt{(x_2-100)^2}$ which has a minimum function value of zero at Cartesian coordinates (100, 100). Many noise removal techniques proposed by Mandal and Mukhopadhyay [23]-[26]. These filters perform excellent when applied to images corrupted with high, medium and low densities of noises. A systematic theory was developed mainly by Donoho and Johnstone[27]. Chang S. G. And B. Yu et. al. observed these observations are consistent with the nature of adaptive processes[28] Kennedy & Eberhart considered the global minimizer of their test function as a type of corn field and were curious to see whether the swarm of particles would successfully flock toward the food. As the swarm flocked toward location (100, 100), this algorithm mimicking the social interaction of swarming or schooling creatures was verified to be an optimization algorithm. Since that time, PSO has been shown to converge quickly relative to other population-based optimization algorithms such as GA while still offering good solution quality [29] [30].

Next, the basic idea behind the wavelet-based developed image denoising methods will be briefly described.

III. PROBLEM IDENTIFICATION

Image denoising is an important image processing task, both as a process itself, and as a component in other processes. many ways to denoise an image or a set of data exists.Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. In this we describes 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 instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model.

Denoising used for remove the noise from corrupted images. Noise corrupts the original image and qualityof image degraded. There are many filters used fordenoise the corrupted image. Noise corrupts themedical images. There is issue with low frequencyareas, salt and pepper noise and speckle noise. Thereis need to use advance filter to solve that problem.Global optimization and maxima minima problem occurred during the denoising process by using existing mehods. To overcome this problem we proposed Particle Swarm Optimization algorithm.

IV. METHODOLOGY

Image denoising is one of the most essential task in image processing.Two different technique of threshold estimation can be used for image denoising.These are BayesShrink and Particle Swarm Optimization algorithm.Using some statistical parameter such as MSE, PSNR we cancalculate the amount of information retained in the denoising image compare to original image. Good estimation of the wavelet parameters such as wavelet function, decomposition level and threshold value is important to the success of wavelet based denoising. These parameters are usually estimated in empirical or semiempirical manner during the denoising the corrupted images. This procedure does not guarantee to achieve the optimal restoration results. To overcome this problem, we adds one randomized optimization algorithm to this.In this paper proposed a wavelet denoising technique which is based on BayesShrink threshold technique and one population based optimization algorithm i.e Particle Swarm Optimization(PSO),which solves the problem of global optimization. Threshold selection is extremely important in wavelet transform for image denoising. It can overcome the inherent deficiency of conventional morphological operations, adaptively obtain the size of the structuring element, and effectively remove impulse noise from images, especially for the image whose signal to noise ratio value is relatively low. So it has a good prospect in image processing.

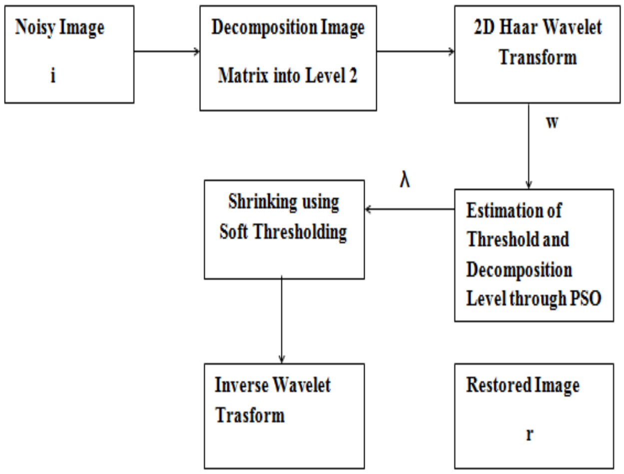


Fig.4.1: Block diagram of Proposed Technique

4.1 Algorithm for Image denoising

Step 1: Take an original image.

Step 2: Decompose the noisy image into level 2.

Step 3: Add different variance of noise (Gaussian , Salt and pepper ,Speckle) with original image.

Step 4: Applying 2D haar wavelet transform,after that we get wavelet coefficients.

Step 5: Threholding operation is done on wavelet transformed coefficients of the noisy image for suppression. This operation is performed by the PSO algorithm.

Step 6: After that the threshold value is transferred to the soft thresholding ,in which the coefficients which are higher than the threshod are reduced by an amount equal to the value of threshold ,otherwise they are set to zeroes.

Step 7: Inverse discrete wavelet transformation is performed.

Step 8: Compare the restored image that obtained in step 6 with original image and estimate statistical parameters like, MSE and PSNR

4.2 Techniques Used for Image Denoising

1) BayesShrink
2) Particle Swarm Optimization Algorithm

1) 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

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

This method defines the rules of applying the threshold to the wavelet coefficients. The threshold is compared to all coefficients of the wavelet domain and when the coefficients are less than the threshold value they are assigned zero values, otherwise they are kept unaltered. The reason behind it is that small coefficients are supposed to be not of signal elements and so can be modified to zeroes. The large coefficients are supposed to be of important signal features band. It also finds a threshold which minimizes the Bayesian risk.

2) Particle Swarm Optimization

- **PSO Concepts**

• The PSO algorithm maintains multiple potential solutions at one time.

• During each iteration of the algorithm, eachsolution is evaluated by an objective function to determine its fitness.

• Each solution is represented by a particle in the fitness landscape (search space)

• The particles "fly" or "swarm" through the search space to find the maximum value returned by the objective function.

- **Each particle maintains:**

• Position in the search space (solution and fitness)
• Velocity
• Individual best position
• In addition, the swarm maintains its global best position

- **The PSO algorithm consists of just three steps:**

1. Evaluate fitness of each particle
2. Update individual and global bests
3. Update velocity and position of each particle

These steps are repeated until some stopping condition is met.

- **Velocity Update**

Each particle's velocity is updated using this equation :

$$v_i(t+1) = wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)]$$

Where,

- i is the particle index
- w is the inertial coefficient
- c_1 and c_2 are acceleration coefficients, $0 \le c_1, c_2 \le 2$
- r_1 and r_2 are random values ($0 \le r_1, r_2 \le 1$) regenerated every velocity update.
- $v_i(t)$ is the particle's velocity at time t
- x_i (t) is the particle's velocity at time t
- x_i^(t) is the particle's individual best solution as of time t
- g(t) is the swarm's best solution as of time t

- **Position Update**

Each particle's position is updated using this equation:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

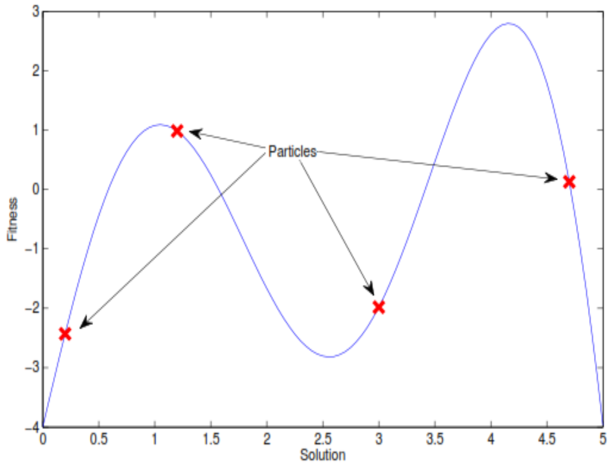


Figure 4.3 : Fitness Landscape

Particle swarm optimization is an extremely wimple algorithm that seems to be effective for optimizing a wide range of functions. We view it as a]mid-level form of A-life or biologically derived algorithm,occupying the space in nature between evollutionary search, which requires eons,and neural processing,which occurs on the order of milliseconds. Social optimization occursin the time frame of ordinary experience- in fact,it is ordinary experieince. In addition to its ties with A-life, particle swarmoptimization has obvious ties with evolutioiniuy computation.

4.4.2 PSO Algorithm Steps :

Step 1: Generate initial population.
Step 2: Evaluate the fitness values of each particle.
Step 3: Update the values of pbest and gbest according to the calculated fitness values.
Step 4: If the position of the global best particle is denoted by gbest, then the velocity updates are calculated by using the equation (4.2)

$$v_i(t+1) = wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)]$$

Step 5: Then the position of particle is updated by using the equation (4.3) $x_i(t+1) = x_i(t) + v_i(t+1)$

Step 6: If the termination criteria met, then we stop the procedure,otherwise we go to step 1 and repeat the steps until the termination criteria is met.

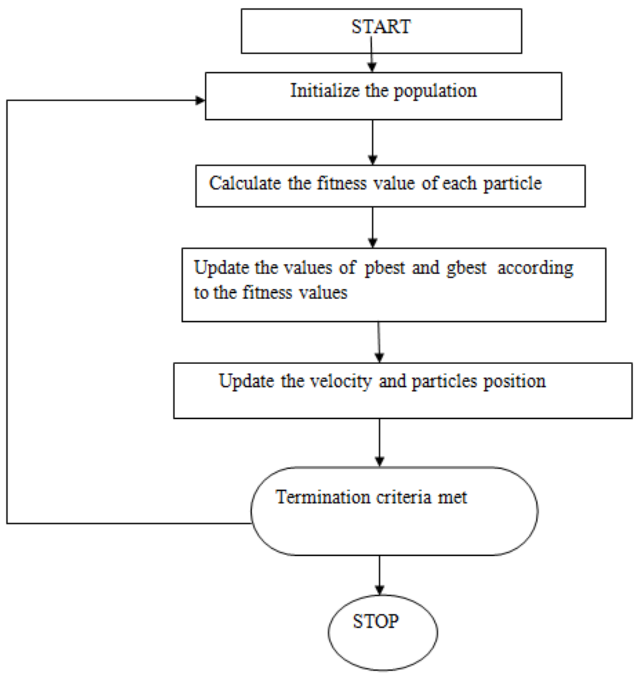


Figure 4.4: Flowchart of the PSO Algorithm

Each particle (or agent) evaluates the function to maximize at each point it visits in spaces.Each agent remembers the best value of the function found so far by it (pbest) and its co-ordinates.Secondly, each agent know the globally best position that one member of the flock had found, and its value (gbest). Using the co-ordinates of pbest and gbest, each agent calculates its new velocity. Update the velocity and position of each particle. The particles in the swarm co-operate. They exchange information about what they've discovered in the places they have visited.First, confirm that you have the correct template for your paper size.

V. RESULT AND DISCUSSIONS

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 five runs. Since the main comparison is against BayesShrink and PSO, the better one among these. PSO outperforms BayesShrink most of the time in terms of PSNR as well as in terms of visual quality.In proposed method, not only PSNR is enhanced ,but also the picture quality and vision are improved. moreover it bigger along with the nois variance, the PSNR and image quality is better.

- It can effectively remove impulse noise from images, especially for the image whose signal to noise ratio value is relatively low. So it has a good prospect in image processing.
- The proposed method efficiently suppresses the Gaussian noise with low medium and high densities. We also Improved the following:

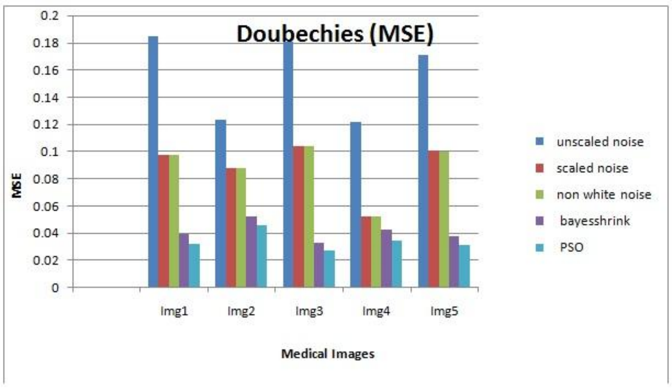
  - Maxima Minima problem
  - MSE
  - PSNR

Images/Methods	Img 1	Img 2	Img 3	Img 4	Img 5
Unscaled noise	0.1844	0.1231	0.1808	0.1217	0.1709
Scaled noise	0.0978	0.0876	0.1037	0.0523	0.1007
Non white noise	0.0979	0.0878	0.1037	0.0523	0.0997
Bayes Shrink	0.0397	0.0528	0.0334	0.0426	0.0375
PSO	0.0319	0.0457	0.0278	0.0347	0.0317

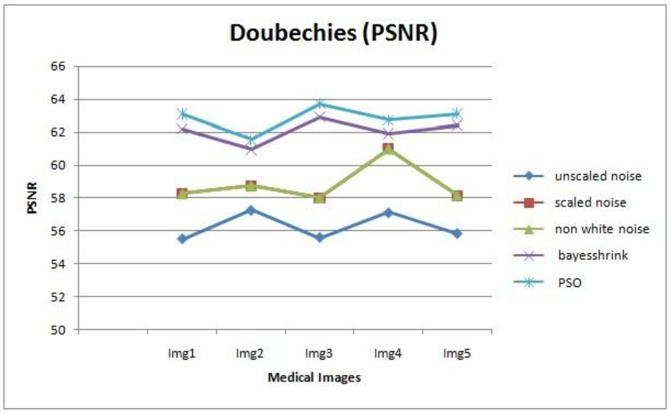
Table 5.1 : Comparisons of results in terms of MSE for Primary brain tumor image corrupted by Gaussian noise. (Doubechies)

Images/Methods	Img 1	Img 2	Img 3	Img 4	Img 5
Unscaled noise	55.5072	57.2616	55.5919	57.1064	55.8356
Scaled noise	58.2621	58.7357	58.0084	60.9814	58.1314
Non white noise	58.2589	58.7292	58.0082	60.9805	58.1758
Bayes Shrink	62.1796	60.9375	62.9211	61.906	62.4213
PSO	63.0999	61.5624	63.7302	62.7645	63.1493

Table 5.2 : Comparisons of results in terms of PSNR for Primary brain tumor image corrupted by Gaussian noise. (Doubechies)

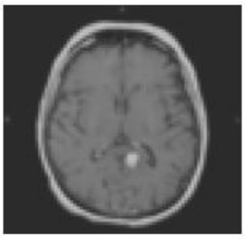


(a) Comparison graph of different thresholding methods based on MSE .

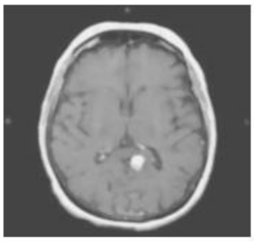


(b)Comparison graph of different thresholding methods based on PSNR

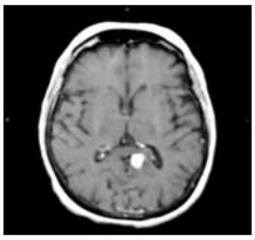
Figure 5.1: Results of the denoising methods for the different images of primary brain tumor (a)-(b) illustrate the graph based on MSE and PSNR of the original to denoised images.(Doubechies)



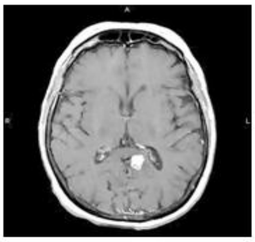
(a) Unscaled Noise
MSE= 0.1709 ,PSNR=55.8356



(b) Scaled Noise
MSE= 0.1007 , PSNR=58.1314



(c) BayesShrink
MSE=0.0375 , PSNR=62.4213



(d) PSO
MSE = 0.0317 , PSNR=65.4213

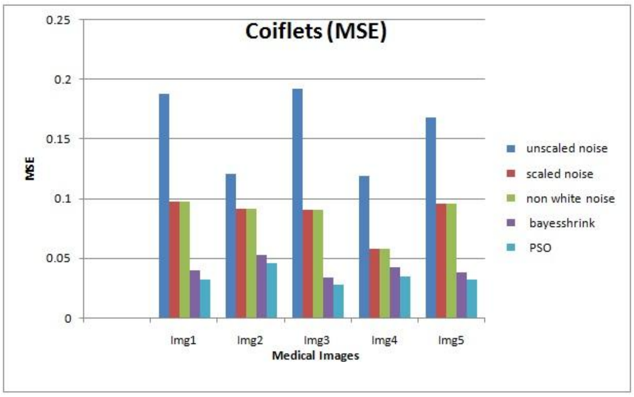
Figure 5.2: The primary brain tumor image in which ,applying the various thresholding methods (Doubechies)

Images/Methods	Img 1	Img 2	Img 3	Img 4	Img 5
Unscaled noise	0.1882	0.1208	0.1923	0.1192	0.1682
Scaled noise	0.0977	0.0913	0.0901	0.0577	0.0954
Non white noise	0.0978	0.0914	0.0902	0.0578	0.0955
Bayes Shrink	0.0397	0.0528	0.0334	0.0426	0.0375
PSO	0.0319	0.0457	0.0278	0.0347	0.0317

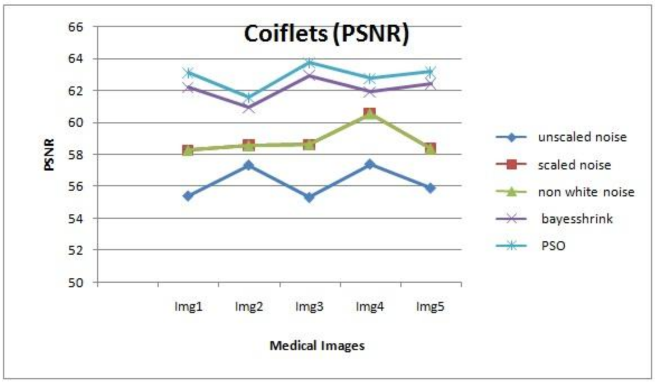
Table 5.3 : Comparisons of results in terms of MSE for Primary brain tumor image corrupted by Gaussian noise.(Coiflets)

Table 5.4 : Comparisons of results in terms of PSNR for Primary brain tumor image corrupted by Gaussian noise.(Coiflets)

Images/Methods	Img 1	Img 2	Img 3	Img 4	Img 5
Unscaled noise	55.4191	57.3434	55.3251	57.4039	55.9073
Scaled noise	58.2648	58.5602	58.6187	60.554	58.3675
Non white noise	58.262	58.5551	58.6185	60.5519	58.3617
Bayes Shrink	62.1796	60.9375	62.9211	61.906	62.4213
PSO	63.0999	61.5624	63.7302	62.7645	63.1493



(a) Comparison graph of different thresholding methods based on MSE .



(b) Comparison graph of different thresholding methods based on PSNR

Figure 5.3: Results of the denoising methods for the different images of primary brain tumor (a)-(b) illustrate the graph based on MSE and PSNR of the original to denoised images.(Coiflets)

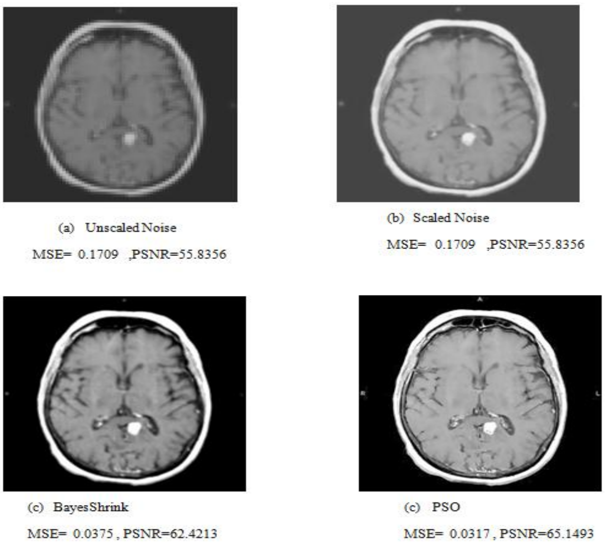


Figure 5.1: The primary brain tumor image in which ,applying the various thresholding mehods(Coiflets)

VI. CONCLUSION AND FUTURE SCOPE

In wavelet based image denoising one thresholding method is applied which is estimated based on either the whole image or based on each sub band of the image.The traditional Bayesian threshold is estimated for each sub band independently. PSO algorithm has been used very effectively to search the pair of wavelet parameters such as the optimal threshold and the value of decomposition level, since these two are the most important parameters of the wavelet denoising technique.Along with the proposed algorithm some other thrsholding methods like Unscaled noise,Scaled noise,non White noise,BayesShrink and the proposed PSO based thresholding techniques have also been implemented. Results obtained demonstrate that the proposed method efficiently suppresses the Gaussian noise with low, medium and high densities. Experimental results show that the new thresholding method based on the wavelet transform produces better restoration results in terms of PSNR and visual effects.

6.2 SCOPE OF FURTHER WORK

The current research work indicates the ability of the proposed denoising method. However, further investigations may improved the recovered image under different noise condition. During the research work a few directions for further research have been identified. These are stated below:

- Exploring various thresholding technique in standard image denoising methods.
- Developing restoration technique by using other methods of Swarm Intelligence.

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