CHAPTER 3

IMAGE ENHANCEMENT

3.1 INTRODUCTION

Noise is the undesirable effects produced in the image. In analog and digital electronics, noise is an unwanted degradation in a wanted signal, caused by external disturbance while an image is being captured during image transmission. In DIP, the word noise means, the pixels in the image shows different intensity values instead of true pixel values. Generally, the noise comes from sensors (thermal / physical or electrical interference) based on environmental conditions, Levels of light and sensor temperature are inadequate, interference in the transmission channel may damage the image and dust occurs in the scanner screen may produce the noise in the image (Rohit Verma and Jahid Ali 2013). The main reasons for image de-noising is visually unpleasant, bad for compression and bad for analysis. De-noising means removal of noise (noise reduction) from the signal or image. Noise reduction is an important and basic part in medical imaging. Features extraction and object recognition within the noisy image, the medical diagnosis operation will become difficult. In medical image processing, it is very difficult to perform the task such as image registration, segmentation, fusion, classification in the image which contains a noise constraint. Hence, it is essential of removing the noise from an image is a primary task during the medical image analysis and diagnosis of treatment planning and assessment.
Noise removal method is the procedure of eradicating or minimizing the noise from the medical image and also to reduce or eliminate the visibility of the noise by smoothing all areas of an image, particularly in the region around the boundary areas of an image. Though noise removal algorithm may be applied in an image it becomes ambiguous and low contrast. Noise is a universal problem in the medical image processing. Therefore, a number of researchers and scientists are paying more attention on this field to enhance the current state-of-the-art (Naga Prudhvi Raj and Venkateswarlu 2012).

3.2 NEED FOR THE IMAGE ENHANCEMENT

The physicians are facing the crucial problems in diagnosis the disease of a medical image because those images contain noise components during the image acquisition. So, the physician are induced to remove the noise to enhance the image quality for further analyzing an medical modality images, it is called as pre-processing like image enhancement (de-noising). Medical image enhancement improves the image perception of information for human viewers, to increase the low contrast and minimizing the noise in lower level as well as higher level frequency. Image enhancement is essential for enhancing the appearance and to improve the features contained in the image. Different types of noise may be present during the image conversion from one form to another like image acquisition, copy an image from one place to another, digitized, and image transmission. In case, digitization of the analog image to get the digital image which contains quantization noise; while the image is transmitted through the communication channel, the received image may contain channel noise; once the image is compressed, the resultant image may contain compression error. Hence, the image
enhancement approach must be needed to have removal of the noise artifacts in order to maintain the original structure of the image.

3.3 TYPES OF NOISES

Noise is an image pixel which shows the distinct values of pixel intensity instead of accurate value of pixel. During the image acquisition or transmission, the noise will occur; it can be categorized into the following types. Such as, Impulse noise, Amplifier noise and Multiplicative noise. Each noise has their own individual characteristics so that it can be distinguished from one to others. Here we present some of the major noise models of an image.

3.3.1 Impulse Noise (Salt and Pepper Noise)

Impulse noise is also known as salt and pepper noise. This noise can be caused by un-expected disturbance in the image signal. Its appearance is randomly scattered white or black (or both) pixel over the image. However, in presence of salt and pepper noise, the image is not corrupted completely when replacement by changing the values of some pixels in the image. Even though in noisy image, it does not change all neighbors’ pixels.

During the data acquisition or transmission, the noise occurs in an image. The pixel value of an image is replaced by corrupted pixel values between in the 0 to 255 respectively. Now, consider 3 x 3 image matrices which shown in Figure 3.1.

![Figure 3.1 Part of the pixel value](image)

Suppose the right corner part of value of matrices is corrupted by this noise, the pixel value is replaced by zero. In this relationship, the noise is added with the dead pixels either dark or bright. So, gradually in a salt and
pepper noise dark pixel values are present in bright regions (Joshi et.al. 2014).

### 3.3.2 Amplifier Noise (Gaussian Noise)

Gaussian noise is caused by random fluctuation in the signal. So the random values are added to an image. Gaussian noise is also referred as electronic noise because this noise is an amplifier or detectors type of noise caused by thermal shaking of particles and radiation of temperate objects (Boyat and Joshi 2013). This noise model is additive and pursue the Gaussian distribution, each pixel in the corrupted image is the addition of the proper value of the pixel and a random noise value distributed by the Gaussian. The noise is autonomous of intensity of pixel value at each point.

### 3.3.3 Periodic Noise

Periodic noise is a summation of small blood vessel signals with the similar amplitudes but with random phases. Periodic noise is caused from the electronics interferences. During image acquisition it may cause intrusion from the electronic circuit.

### 3.3.4 Poisson Noise (Photon Noise)

Poisson noise is cause when a number of photons sensed by the sensors is inadequate to provide measurable arithmetical information (Pawan Patidar et.al. 2010). This noise has root mean square value which is proportional to the square root intensity of the image. As realistic reasons the photon and other sensor based noise corrupts the signal at different proportions.

### 3.3.5 Speckle Noise

Speckle noise can be modeled by random values multiplied by pixel values of an image and it can be expressed as \( j = I + n \cdot I \) where \( j \) is the distribution of speckle noise of an image, \( I \) represent the source image and
n is the image of the uniform noise by mean (μ) and variance (σ). This noise deteriorates of active radar quality image (Pawan Patidar et al. 2010). In traditional radar system, the noise is observed when the signal is returned from the object having less in size or equal to a single image unit of processing.

3.4 GAUSSIAN NOISE REPRESENTATION

Digital images can be conveniently represented and manipulated as matrices containing the light intensity or color information at each spatially sampled point. The term monochrome digital image or simply digital image, refers to a two-dimensional light intensity function $f(i, j)$ where $i, j$ denote spatial coordinates, the value of $f(i, j)$ is proportional to the brightness (or gray level) of the image at that point $i, j$ and $f(i, j)$. The problem of image denoising is to recover an image $f(i, j)$ from the observation $g(i, j)$, which is distorted by noise (or noise-like degradation) $q(i, j)$; i.e.,

$$g(i, j) = f(i, j) + q(i, j) \quad (3.1)$$

The original image signal $f_{ij}$ made by the additive Gaussian noise $n_{ij}$ in a particular variance. Each pixel of an image with value of intensity $f_{ij} (1 \leq i \leq M, 1 \leq j \leq N)$ in the size of $M \times N$ in order to get the noisy signal $X_{ij}$.

$$X_{ij} = f_{ij} + n_{ij} \quad (3.2)$$

Each noisy value $n$ is drawn from a zero-mean Gaussian distribution. The image signal is decomposed by the dual tree complex wavelet transform to get the coefficients of real and imaginary parts; it can be formulated as,

$$CW_{R,ij} = CW_{R,f} + CW_{R,n} \quad (3.3)$$
where,

\( CW_{R,I,n} \) is the noisy image co-efficient, \( CW_{R,I,f} \) are the original image and \( CW_{R,I,n} \) are the noisy image. If the noise complex wavelet coefficients are higher than the obtained coefficients to find the suitable threshold value \( T \) based on the proposed threshold technique.

The main motivation of the de-noising is to estimate function \( f \) with minimum Mean Square Error (MSE).

### 3.5 ENHANCED ADAPTIVE THRESHOLDING FUNCTION

Generally, finding the optimum value of thresholding is not an easy task. To develop or improve the efficiency of thresholding functions, a number of researches are being developed and implemented in the various adaptive thresholding functions with shape tuning parameters. The researcher Bhandari et.al proposed a new non-linear thresholding function with three parameters called adaptive thresholding function (Bhandari 2015). In this approach which using the function of polynomial, the coefficients are tuned and produces a good results than the earlier adaptive thresholding function. However, the choice of \( \alpha \) value is fixed as 0.5. When value is 0.5 or lower, the edges boundary information may not be returned (both internal edge and boundary edge). So, a new proposed modified adaptive thresholding function shall be defined by the user itself. The enhanced adaptive thresholding function is given in the Equation (3.4).

\[
\eta_{(x,\alpha,m,n,k;\alpha)} = \begin{cases} 
  x + (k - 1)T - \frac{\alpha k x^m}{x^m + 1}, & x > T \\
  \alpha k \frac{k x^{n+1} + 1}{k x^{n+1} + 1}, & |x| \leq T \\
  x - (k - 1)T - \frac{\alpha k (x-T)^m}{x^m + 1}, & x < -T 
\end{cases} 
\]  

\[(3.4)\]

where,
\( \mathbf{x} \) is a DT-CWT noisy coefficients, \( T \) is the Threshold value, \( \alpha \) represents the user defined value, \( n \) and \( m \) are used to estimate the shape functions for coefficients of DT-CWT which includes lower and upper value as compared to complete threshold value. \( k \) is the positive integer that is used to compute the function, parameter is varying by \( k \rightarrow \infty \) and \( \alpha \) represent the variants in the shape of thresholding function.

The Enhanced adaptive thresholding function involves three shape tuning parameters for launching the function. The optimization process is substituted using the DT-CWT thresholding function and the weights of the optimization are replaced by the threshold value of the thresholding parameters.

3.6 MODIFIED LION OPTIMIZATION TECHNIQUE (MLOT)

Over the past few years, a lots of researches are being developed in optimization techniques with sub band adaptive thresholding function such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), JADE etc. which are in medical image de-noising, all of them offer good results for de-noised image which improves the image quality. In JADE with adaptive thresholding approach gives a better result even at higher level. However, the thresholding value and the thresholding function is not been obtained simultaneously and it is not suitable for edge preserving for the Gaussian noise. So, a new proposed system by using the modified LION Optimization Technique (mLOT). The basic information of the proposed method comes from the LION optimization algorithm (Maziar Yazdani and Foriforz Jolai 2015).

The procedure of the proposed mLOT optimization technique is summarized as follows.
Step 1: Initialization:

a. Set the number of lions (populations) as \( N \) that will be generated randomly within the solution space. Each solution is called ‘lion’ (region/segment). The lion is represented by dimensional optimization problem as,

\[
\text{Lion} = X = (x_1, x_2, ..., x_N) \quad (3.5)
\]
\[
f(X) = f(x_1, x_2, ..., x_N) = f(x_{i1}, x_{i2}, ..., x_{iN}) \quad (3.6)
\]

where,

\( f(X) \) represent the fitness value (cost) of lion, \( x_i \) is the single region and \( x_N \) is the number of regions i.e. 0...L-1 (L is the 256).

b. The whole initial lions choose the nomad lion (NML) for certain percentage at randomly and rest of the lion will be split into several groups called as Prides (\( P \)).

c. In each pride, the female lion (FL) and male lion (ML) are in equal percentage.

d. For NML, the FL and ML should form equal percentage.

Step 2: Hunting:

a. In each pride, some female lions have to been selected for hunting process and rest of female lions are set to the best positions for searching place.

b. Calculate the fitness value (\( \beta \)) of female hunters (FH) based on the following equation as,

\[
\beta = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} [(i,j) - \bar{r}(i,j)]^2 \quad (3.7)
\]
Here, \( m, n \) is the size of sub-band image; \( I \) is the original sub-band image and \( \bar{I} \) is the noised sub-band image.

Then calculate the Prey (Pr) using the Equation (3.8).

c. Calculate the fitness value (\( \beta \)) of hunters on female lion, Calculate the p (prey) based on the given formula of standard deviation (i.e. sum of the average fitness value of the hunting female) and set in the p in center of the n(FH), where n(FH) is the number of female hunters.

\[
Pr = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} (x_i - \mu)^2
\]  

(3.8)

where, 

\( N \) is the number of hunters, \( x_i \) is the single hunter and \( \mu \) is the sum of hunters.

Then set the Pr in center of the n(FH), here n(FH) is the number of female hunters.

d. Thought the hunting process, the hunter improves the fitness cost (\( \lambda \)). i.e.

\[
\lambda = Pr - FH
\]  

(3.9)

During the process, disturbance ‘Dt’ is associated with in the hunters, it may reduce the \( \lambda \) when compared with \( \beta \), and then detect and remove the disturbance.

\[
\beta = \lambda + Dt
\]  

(3.10)

Now, Pr will get away from hunters and move on to the new position.

\[
Pr' = Pr + R(0, 1) \times \lambda \times (Pr - FH)
\]  

(3.11)

\( \lambda \) is the improvement of the fitness cost for hunters.
Step 3: Moving to the safe place: In each pride, the remaining female lion (FL) in the territory place will calculate the current and the new position fitness value ($\beta$ and $\beta'$)

$$H' = \begin{cases} R(FH, Pr), & \text{if } FH < Pr \\ R(Pr, FH), & \text{if } FH > Pr \end{cases} \quad (3.12)$$

$$FL' = FL + C(\bar{R}(0,1)) \times FL \quad (3.13)$$

$$FL' = \begin{cases} \beta', & \text{if } \beta < \beta' \\ \beta, & \text{otherwise} \end{cases} \quad (3.14)$$

where,

$C$ is the constant value between the 0 and 1.

Step 4: Roaming: in each male lion (ML) in a pride, due to some reasons the lions will be roaming in territory. Select the male lion in the roaming and check if it is mad lion (MDL) or nomad lion (NMDL). If it is MDL, estimate the $\beta$ current and select the new position randomly.

$$ML' = \begin{cases} \text{current} \beta, & \text{if current} \beta > \text{new} \beta \\ \text{new} \beta, & \text{otherwise} \end{cases} \quad (3.15)$$

Otherwise this is the NMDL; estimate the probability of all by using the given equation.

$$PrO_i = 0.1 + \min \left(0.5, \frac{NMD_i - \text{bestNMDL}}{\text{bestNMDL}}\right), i = 1, 2, \ldots \quad (3.16)$$

Step 5: Mating: set the female lion (FL) with all pride for mating to all male in all pride and produce the new lions (twos) c.

$$c_{j,1} = ND \times FL_j + \sum_{i=1}^{(1-N)} \frac{N}{2} \times ML^i_j \times S_i \quad (3.17)$$

$$c_{j,2} = 1 - ND \times FL_j + \sum_{i=1}^{(N)} \frac{N}{2} \times ML^i_j \times S_i \quad (3.18)$$
where, \( j \) is the dimension, 
\[
S_i = \begin{cases} 
1, & \text{if} \ male = i \\ 
0, & \text{otherwise} 
\end{cases}
\]

ND is the randomly generated numbers by normal distribution with \( \mu \) and \( \sigma \), i.e. \( ND(0,1) \) and \( NR \) represents the number of residential male and ND is the normal distribution.

Step 6: Defense: To evaluate the \( \beta \) of mad and nomad of the male lion and will choose the best, by using the given equation (3.19).

\[
ML = \begin{cases} 
NML, & \text{if} \ NML > ML \\ 
ML, & \text{otherwise} 
\end{cases}
\]  

(3.19)

Step 7: Migration: In each pride, females select randomly to become a nomad when female lions are migrated to some other area.

Step 8: Equilibrium: At the end of the search iteration. The number of live lions will be controlled and remove the worst \( \beta \) of the nomad with respect of the maximum permitted.

Step 9: Consider, the stopping conditions are assumed as the CPU time or number of iteration without improvements are not satisfied the go to step 2 for hunting otherwise the process will be stopped.

### 3.7 PROPOSED DE-NOISING METHOD

The proposed de-noising method will eliminate the Gaussian noise to the maximum extent. The performance of the mLOT with Enhanced Adaptive Thresholding Function (EATF) techniques are measured in terms of MSE, PSNR, and SSIM. A randomized search algorithm will provide an accurate threshold value of the decomposition levels. The block diagram of these proposed algorithms is given in the Figure 3.2.
The source image and the noisy image are decomposed using the DT-CWT up to n level to get the low and high frequency coefficients respectively. Then the low frequency coefficients are put into the proposed mLOT based optimization algorithm to obtain solution and passed to the new enhanced adaptive thresholding function to get the best solution for each sub bands at each level. Finally, these coefficients are reconstructed by the inverse DT-CWT to get the de-noised image. The detailed steps of the proposed de-noising algorithm are as follows.

Step 1: The original registered medical images of size m x n are added with Gaussian noise $n_{ij}$ for pre-determined variance.

Step 2: Decompose the given image using Dual-Tree Complex Wavelet Transform up to n level and to get two low frequency sub bands and six high frequency sub bands in each level on both real and imaginary parts.

$$\left\{ (L_t^l(i,j), H_{l,d}^l(i,j)) : l = n, t = 1,2, d = 1 \ldots 6 \right\} \quad (3.20)$$

Here, $L_t^l(i,j)$ are the low frequency sub bands in the t orientation $H_{l,d}^l(i,j)$ represents a high frequency sub bands in level2 d orientation.
Step 3: Place the necessary parameters for the LION optimization algorithm such as number of iteration, number of population, and the number of dimensions etc.

Step 4: At present put the noisy coefficients of all level to the new mLLOT algorithm.

Step 5: To obtain the solutions from the mLLOT algorithm, estimate the fitness value for each solutions and for each sub-bands of noisy images based on equation no. 3.5.

Step 6: Obtain the best solutions by the $x, \lambda, m, n, k, \alpha$ based on mLLOT and passed it to the thresholding function with noisy coefficients to get required composite coefficients.

Step 7: To apply the inverse DT-CWT for these coefficients matrices to get the de-noised image.

Step 8: Estimate the essential Quality metric parameters such as MSE, PSNR, and SSIM.

3.8 EXPERIMENTAL RESULTS

The proposed technique is one of the vital ingredients of our Multimodal Medical Image De-noising (MMID). The performance of the proposed mLLOT algorithm has been appraised quantitatively and qualitatively based on simulation and examination. A variety of optimization algorithms like Genetic algorithm (GA) (Somnath Mukhopadhyaya and Mandal 2013), Particle Swarm Optimization (PSO)(Bhutada et.al. 2012), JADE (Bhandari 2015) along with the mLLOT with different noise variances are being implemented on grey scale medical image for anatomical images like CT, MRI and the functional images like PET and SPECT. These algorithms have been implemented and assessed in MATLAB 15a environment and to show the different graphical demonstration of the results. Based on the existing experimental methodologies, the proposed algorithm offer fine results and it has been tested for best well-matched in medical image. The anatomic and
functional images are trained with different noising variance with Gaussian noise and the performance indices of time required attaining the proposed algorithm measured by MSE, PSNR and SSIM.

PSNR and MSE are directly depend on the image intensity values, which includes the accuracy of the inverse image and the MSE represents the cumulative squared error between the original image and the final de-noised image. The error of the de-noised image is lower when the MSE value is low. In this research it is used to evaluate the performance of an image in terms of the below significant parameters.

\[
MSE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} [I(i,j) - \hat{I}(i,j)]^2
\]  \hspace{1cm} (3.21)

\[
PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right)
\]  \hspace{1cm} (3.22)

where,

m and n are the size of the image, I is the original image and \( \hat{I} \) is the denoised image with a particular noise variance.

In additional, the SSIM is an image quality assessment based on the degradation of structural information, it is used to measure the similarity among the original image and de-noised image which is also used to compare the structure of the original and threshold images which is expressed as (Bhandari et.al. 2015).

\[
SSIM = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{\mu_x^2 + \mu_y^2 + C_1(\sigma_x^2 + \sigma_y^2 + C_2)}
\]  \hspace{1cm} (3.23)

where,

\( \mu_x \) and \( \mu_y \) represents mean intensity ofthe images x and y respectively. \( \sigma_x \) and \( \sigma_y \) Indicates the standard deviation of x and y respectively. \( \sigma_{xy} \) which means the local correlation between x and y. \( C_1 \) and \( C_2 \) are the constants, it takes the value between [-1, 1] range and its value is higher, will the expected results of performance is superior.
To examine the effectiveness of the proposed optimization is based on enhanced adaptive thresholding approach and also different existing image de-noising methods with corrupted images by Gaussian noise are considered and compared with the original image. The Gaussian noise is added to the various medical input images with different noise variance such as $\sigma=10$, $\sigma=20$ $\sigma=30$ and $\sigma=60$, images can be decomposed by Dual-Tree Complex Wavelet Transform up to $n$ ($n=2$) level. Various medical images of different modalities like CT, MRI, PET, and SPECT are as shown in Figure 3.3.

![Input images of various modalities like CT, MRI, PET, and SPECT](image1)

**Figure 3.3** Input images of various modalities like CT, MRI, PET, and SPECT

The corrupted noise images (Gaussian noise) of different medical modalities such as CT, MRI, PET, and SPECT with different noise variance are shown in Figure 3.4.
Figure 3.4  Noised images with Gaussian Noise: (a1-a4) is 10, (b1-b4) is 20, (c1-c4) is 30 and (d1-d4) is 60

The proposed scheme obtains good results on de-noised image with higher quality of features; the thresholding function is used in sub-band adaptive scenario using modified LOT optimization technique. In this optimization approach, only the threshold value is learnt and shape tuning factors ($x, T, \alpha, m, n, k$) of functions are kept fixed and $\alpha$ is a dynamic.

The input images were tested using some standard optimization techniques along with proposed algorithm with different noise variance. Figure 3.5 shows the de-noised image of input image on CT with various noise variance using a new mLOT optimization and Enhanced Adaptive Thresholding Function (EATF) approach.
Figure 3.5 Simulation Results in the de-noised image of CT: (a1-a4) is based on GA; (b1-b4) is based on PSO; (c1-c4) is based on JADE and (d1-d4) is based on proposed mLOT.

The Figure 3.6 shows the corresponding conversion rate with respect to MSE for each optimization based on de-noising methods such as GA, PSO, JADE along with new proposed mLOT algorithm with various noise variance of the input image on CT.
Figure 3.6 Comparative performance of the MSE convergence rate (Fitness) for GA, PSO, JADE and new mLOT optimization and Enhanced Adaptive Thresholding Function (EATF) approach with different noise variance (Gaussian noise) for the input image on CT.
Table 3.1 MSE, PSNR and SSIM results the comparison for various input images and different noise variance values with different optimization and mLOT algorithm based on sub-band adaptive thresholding function for the input image on CT.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Algom.</th>
<th>Quality Metrics</th>
<th>Noise Variance</th>
<th>σ=10</th>
<th>σ=20</th>
<th>σ=30</th>
<th>σ=60</th>
</tr>
</thead>
<tbody>
<tr>
<td>CT</td>
<td>GA</td>
<td>MSE</td>
<td></td>
<td>107.7328</td>
<td>148.5541</td>
<td>136.1175</td>
<td>347.8578</td>
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<tr>
<td></td>
<td></td>
<td>PSNR</td>
<td></td>
<td>27.8073</td>
<td>26.412</td>
<td>26.7917</td>
<td>22.7168</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SSIM</td>
<td></td>
<td>0.8098</td>
<td>0.6929</td>
<td>0.5961</td>
<td>0.443</td>
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<tr>
<td>PSO</td>
<td>GA</td>
<td>MSE</td>
<td></td>
<td>69.1979</td>
<td>124.3892</td>
<td>114.7936</td>
<td>342.617</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PSNR</td>
<td></td>
<td>29.7299</td>
<td>27.183</td>
<td>27.5316</td>
<td>22.7827</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SSIM</td>
<td></td>
<td>0.8018</td>
<td>0.748</td>
<td>0.5933</td>
<td>0.525</td>
</tr>
<tr>
<td>JADE</td>
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<td>MSE</td>
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<td></td>
<td></td>
<td>PSNR</td>
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<td></td>
<td></td>
<td>SSIM</td>
<td></td>
<td>0.8553</td>
<td>0.707</td>
<td>0.613</td>
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<tr>
<td>mLOT</td>
<td>GA</td>
<td>MSE</td>
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<tr>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>SSIM</td>
<td></td>
<td>0.8532</td>
<td>0.7137</td>
<td>0.6181</td>
<td>0.3669</td>
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</table>

The Figure 3.7 shows the de-noised images of the input images on MRI, which includes different noise intensity (Variance) with Gaussian noise using the existing standard optimization techniques with a new mLOT optimization and Enhanced Adaptive Thresholding Function (EATF) approach.
Figure 3.7  Simulation Results in the de-noised image of MRI: (a1-a4) is based on GA; (b1-b4) is based on PSO; (c1-c4) is based on JADE and (d1-d4) is based on proposed mLOT.
The Figure 3.8 shows the corresponding conversion rate with respect to MSE for each optimization based de-noising methods such as GA, PSO, JADE along with new proposed mLOT algorithm with various noise variance of the input image on MRI.

**Figure 3.8** Comparative performance of the MSE convergence rate (Fitness) for GA, PSO, JADE and new mLOT optimization and Enhanced Adaptive Thresholding Function (EATF)
approach with different noise variance (Gaussian noise) for the input image on MRI.

Table 3.2 MSE, PSNR and SSIM shows the results comparison for various input images, different noise variance and the values of different optimization and mLOT algorithm based on sub-band adaptive thresholding function for the input image on MRI.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Algom.</th>
<th>Quality Metrics</th>
<th>Noise Variance</th>
</tr>
</thead>
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<td></td>
<td></td>
<td>(\sigma=10)</td>
</tr>
<tr>
<td>MRI</td>
<td>GA</td>
<td>MSE</td>
<td>143.5393</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PSNR</td>
<td>26.5611</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SSIM</td>
<td>0.73</td>
</tr>
<tr>
<td>PSO</td>
<td>MSE</td>
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</tr>
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<td></td>
<td>SSIM</td>
<td>0.7963</td>
<td>0.6387</td>
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The Figure 3.9 shows the de-noised images of the input images on PET, which includes different noise intensity (Variance) with Gaussian
noise using the existing standard optimization techniques with a new mLOT optimization approach.

Figure 3.9 Simulation Results in the de-noised image of PET: (a1-a4) is based on GA; (b1-b4) is based on PSO; (c1-c4) is based on JADE and (d1-d4) is based on proposed mLOT.

The Figure 3.10 shows the corresponding conversion rate with respect to MSE for each optimization de-noising methods such as GA, PSO,
JADE along with new proposed mLOT algorithm with various noise variance of the input image on PET.

Figure 3.10 Comparative performance of the MSE convergence rate (Fitness) for GA, PSO, JADE and new mLOT optimization and Enhanced Adaptive Thresholding Function (ATF) approaches the different noise variance (Gaussian noise) for the input image on PET.
Table 3.3 MSE, PSNR and SSIM results the comparison for various input images, different noise variance and the values of different optimization and mLOT algorithm based on sub-band adaptive thresholding function for the input image on PET.

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Algom.</th>
<th>Quality Metrics</th>
<th>Noise Variance</th>
</tr>
</thead>
<tbody>
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<td>PET</td>
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In Figure 3.11 shows the de-noised images of the input images on SPECT, which includes different noise intensity (Variance) with Gaussian noise using the existing standard optimization techniques with a new mLOT optimization approach.
Figure 3.11 Simulation Results in the de-noised image of SPECT: (a1-a4) is based on GA; (b1-b4) is based on PSO; (c1-c4) is based on JADE and (d1-d4) is based on proposed mLOT.

The Figure 3.12 shows the corresponding conversion rate with respect to MSE for each optimization based de-noising methods such as GA, PSO,
JADE along with new proposed mLOT algorithm with various noise variance of the input image on SPECT.

Figure 3.12 Comparative performance of the MSE convergence rate (Fitness) for GA, PSO, and JADE and new mLOT optimization of Enhanced Adaptive Thresholding Function (EATF) approach with different noise variance (Gaussian noise) for the input image on SPECT.
Table 3.4 MSE, PSNR and SSIM results the comparison for various input images, different noise variance and the values of different optimization and mLOT algorithm based on sub-band adaptive thresholding function for the input image on SPCET.

<table>
<thead>
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<th>Noise Variance</th>
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<tr>
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<td></td>
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This approach is order to overcome the shortcoming of LION, female hunters are being selected randomly one behind another to attack the prey. During this time if any disturbance in occur the chance of fitness cost is varied and move to some other location in the searching space based on image
application. The proposed approach is modified, so as to avoid this type of situation. In addition, one more shortcoming of LION is to overcome of the percentage of female and male lion of the each pride which is shared by the equal contribution. In this work, the proposed de-noising approach presents the novel and innovative idea of the new modified optimization technique with enhanced adaptive thresholding functions used for the medical image de-noising, to overcome the existing techniques for obtain the fine quality of de-noised image with better edge preserved.

This work, improving the de-noising scheme for adopting multimodal medical images corrupted with Gaussian noise in the presence of existing classical optimization techniques such as GA, PSO, JADE along with proposed scheme for learning of parameters of sub band adaptive thresholding functions required in optimum performances. A remarkable point is that the Gaussian noise reductions of the given level of noise variance will be considered. The proposed method has been tested in several medical images of CT, MRI (MRT1 and MRT2). The reliability parameters obtained clearly which shows superior of the proposed approach over other conventional and state-of-the-art image de-noising algorithms. Even though, a new noise reduction algorithm is implemented to improve the visual quality of the medical image with in the physician acceptable level. Using the assessment of the patient disease, a physician has to examine and analysis in various multimodal medical images comes from same or different modality with different setting. It would be very much helpful for a physician to further processing of medical image analysis like image fusion. A comparative study of different algorithms has been made, it has been found that the proposed methods based on mLOT with DTCWT yields a better performance which compared with other de-noising methods and their variants are shown on the basis of MSE, PSNR and SSIM performance evaluations to prove the visual effects.