Noise Cancellation in Computed Tomography Images through Adaptive Multi-Stage Noise Removal Paradigm

Jenita Subash, Dr.Kalaivani S*
School of Electronics Engineering (SENSE)
Vellore Institute of Technology, Vellore, Tamil Nadu, India

***Abstract*—Image de-noising is a noise removal approach, which is utilized to remove noise from the noisy image and is utilized to protect the significant features of images namely, corners, edges, textures, and sharp structures. For medical diagnosis Computer tomography (CT) images are mainly utilized. Due to acquisition and transmission in CT imaging, the noise that appears leads to poor image quality. To overcome this problem, an efficient Noise cancellation in computed tomography images using adaptive multi-stage noise removal paradigm is proposed. The proposed approach consists of three phases namely, Optimal Discrete Wavelet Transform, first stage noise removal using Block Matching, and 3D filtering (BM3D) filter and second stage noise removal using the bilateral filter (BF). Initially, Discrete Wavelet Transform (DWT) is applied to the input image to diminish noise in CT images. In this method, co-efficient ranges are optimally selected with the help of Crow Search Optimization (CSO) algorithm. Secondly, to remove the noise present in the bands, BM3D algorithm is applied. Finally, bilateral filter is applied to the BM3D output image to further enhance the image. The performance of the proposed methodology is analyzed in terms of Peak signal-to-noise ratio (PSNR), Root Mean Square Error (RMSE), and Structural Similarity Index (SSIM). Furthermore, the multi-stage noise removal model obtained gives the best PSNR values compared to other techniques.**

***Keywords*—De-noising; computer tomography; discrete wavelet transform; crow search optimization; bilateral filter**

I. Introduction

An image is a collection of dimensions in two dimensional (2-D) or three dimensional (3-D) spaces [1]. Computer tomography (CT) images usually have noise due to faults in image holding methods. Noise will be removed from images so that the analysis of image elements (e.g., blood vessels, inner folding, or tumors in the human brain) can be completely observed and the upcoming image researches are trustworthy. The image restoration presented appears to be the sharpest possible among the multi-scale image smoothing methods by preserving uniqueness and stability [2]. The medical imaging technology is fetching a valuable section of a huge amount of purpose namely research, diagnosis, and treatment. It has enabled doctors to construct images of patient body for medical objectives [3]. Basically medical images namely X-Ray, CT, MRI, and PET contain the information of

Heart, brain, and nerves but these images are suffered from huge shortcomings, which include the acquisition of noise [4].

The noise is irregular fluctuations that accompany a transmitted signal that tend to obscure the signal that has to make the data to slow down or reduce the clarity or accuracy of the data. Medical images may be clear, sharp, noisy and vague. Usually computed tomography (CT) images are distorted by Gaussian noise and salt and pepper noise [5]. The Gaussian noise, which increases due to acquisition and it can be reduced by using spatial filters. Salt and pepper noise, which rarely occurs in form of white and black pixels, can be effectively eliminated by the morphological filter. Two approaches Empirical Mode Decomposition (EMD) and Dual-Tree Complex Wavelet Packets (DTCWP) are used for de-noising the CT-images. All noisy algorithms are based on the local or global noise model and the generalized image softness model [6]. In modern hospitals, X-RAY and CT images are mostly used because these have several importance, but it may lead to potential radiation hazard to patient because x-rays could cause hereditary harm and actuate malignant growth in likelihood identified with radiation portion [7].

A lot of filtering methods for example median filter, mean filter, bilateral filter, Gaussian filter, linear filters, non-linear filters, spatial filters and transform domain filters are used for remove the noise present in the CT images. Moreover, edge-preserving approaches are utilized for reducing undesirable effects on images [18]. In [9] nonlocal means filtering based CT image de-noising is explained in [8] 3D collaborative filtering based de-noising. A lot of methods are available for de-noising even though an efficient de-noising method is urgently needed.

The important goal of this paper is to eliminate noise existing in CT image with the help of multi-stage noise removal paradigm model. The proposed multi-stage noise removal paradigm model consists of two stages of the noise removal process. The first stage noise removal is done with the help of the BM3D filtering algorithm and second stage noise removal is done with the help of a bilateral filter. These two stages have improved the quality of the image. The contribution of the research work is listed below:

- DWT is applied to the input image to convert the spatial domain image into a transform domain. In this, coefficient ranges are optimally selected with the help of CSO algorithm.

*Corresponding Author.

- To evacuate the noise present in the input image BM3D channel is connected to the input image. The BM3D channel accomplishes the dependable PSNR and resolves difficulties of related methodologies when tending to the distinctive level of noise.
- To further progress the input image quality, a bilateral filter is accomplished to output of the BM3D image.
- The performance of proposed technology is scrutinized in conditions of various metrics and performance is in comparison with a different algorithm.

The remainder paper sorted out as pursues; the background of the proposed method is analyzed in Section II and the proposed image de-noising methodology is analyzed in Section III. The performance analysis is discussed in Section IV. Finally the article is concluded in Section V.

II. Background

A lot of researchers had elucidated the image de-noising technique. Among them some of the methods are analyzed here; Elhoseny et al. [10] had proposed a medical image de-noising using optimal bilateral filter (OBF) and convolution neural network (CNN). For the noise removal process optimized bilateral filter (OBF) is utilized. In this filter, Gaussian and spatial weights are the parameter used in the OBF. To increase the characteristic of the de-noised image, the parameters are excellently selected with the help of a combination of dragonfly (DF) and modified fruit fly algorithm. After the filtering process, the normal and abnormal images are classified using CNN classifier. Manduca et al. [11] proposed a novel locally adaptive projection space denoising algorithm for a low dose CT image. Similarly, Katsuhiro et al. [12] have developed an edge preserving based noise reduction using three-dimensional cross-directional bilateral filter (3D-CDBF) in CT images. The filtering process is mainly used for noise removal and edge preserving process. The bilateral filter is a mixture of two types of filters namely spatial and Gaussian filter. Finally, the noise spectrum is calculated for all the de-noised image and performance are analyzed.

In [13], Wojciech and Ewa have explained a medical image noise cancellation and edge preserving based on a granular filter. Here, two different methods namely, crisp and fuzzy are developed. For experimentation, CT and US breast images are utilized. The granular filter performance is compared with different filters namely, relating to space balancing and median, bilateral filter, anisotropic diffusion. Moreover, Hsuan and Chieh [14] have explained a kernel-based image de-noising technique for developing parametric image creation. To eliminate the noise in input image, general-threshold filtering method is combined with a whole variation and this method was investigated. The mathematical explanation of improved intravoxel incoherent motion (IVIM) method based de-noising is proposed. The suggested method was effective than IVIN method.

Manoj and Pardeep, [15] have explained a CT image de-noising using the bilateral method with the concept of Bayes Shrinkage rule in the wavelet domain. Initially, the image is filtered with the help of the bilateral filter. After the noise removal process, wavelet packet based thresholding is applied. Then, to attain the efficient de-noised image, the threshold output image is added with the bilateral filter. The performance of the presented technology is analyzed in conditions of the PSNR and similarity measures. Similarly, in [16], Manoj et al., have explained CT image de-noising in the curvelet domain. In high frequency coefficients, inter- and intra-scale responsibilities are used in side by side. From the high frequency coefficients, correlation values are obtained. Then, both the high frequency coefficients, aggregation are performed. After aggregation, the inverse curvelet transform is applied to get a de-noised image. Moreover, Bing et al. [17] have explained a Coupling de-noising methods depends on individual wavelet transform and modified median filter for medical image. The method consists of four phases namely, image acquisition, image storage, image processing, and image reconstruction. Initially, the image is captured from the patient that contained the noise. Then the collected images are stored on the cloud. In the third phase, the medical image is breakdown into four modules namely, LL, LH, HL, and HH. Then, for further processing, high frequency co-efficient are utilized. Then the changed median filter is applied to three high frequency sub bands. Finally, they have obtained the de-noised image. The performance is analyzed in terms of PSNR measures. Jenita Subash et. al. [19], Shyna.A et.al.[20], Devinder Singh et. al. [21] introduced improved fuzzy based approach for noise removal.

III. Adaptive Multistage Noise Removal Methodology

In this work, a novel multi-stage noise removal paradigm to deal with noise is proposed. The overall architecture of proposed method is shown in Fig. 1. For de-noising process, at first, images are decomposed with the help of DWT. To enhance the sensitive regions with higher visual quality, initially, DWT is employed to input image; while optimal coefficients are selected using the Crow Search Optimization algorithm. After decomposition, BM3D filtering algorithm is applied to high frequency sub bands of DWT output. Then at the subsequent stage, the bilateral filter is used to take out the noise cleanly and it retains the uncorrupted information. The overall concept is compressed into three phases:

A. Crow Search Optimization Algorithm

The most important goal of this section is to segregate the input image into four sub divisions, that is, LL, LH, HL, and HH. To increase the image quality in terms of PSNR, this methodology optimally selects the wavelet coefficient. For wavelet co-efficient optimization, CSO algorithm is utilized. CSO is a recently developed metaheuristic algorithm and also developed based on crow's behaviour.

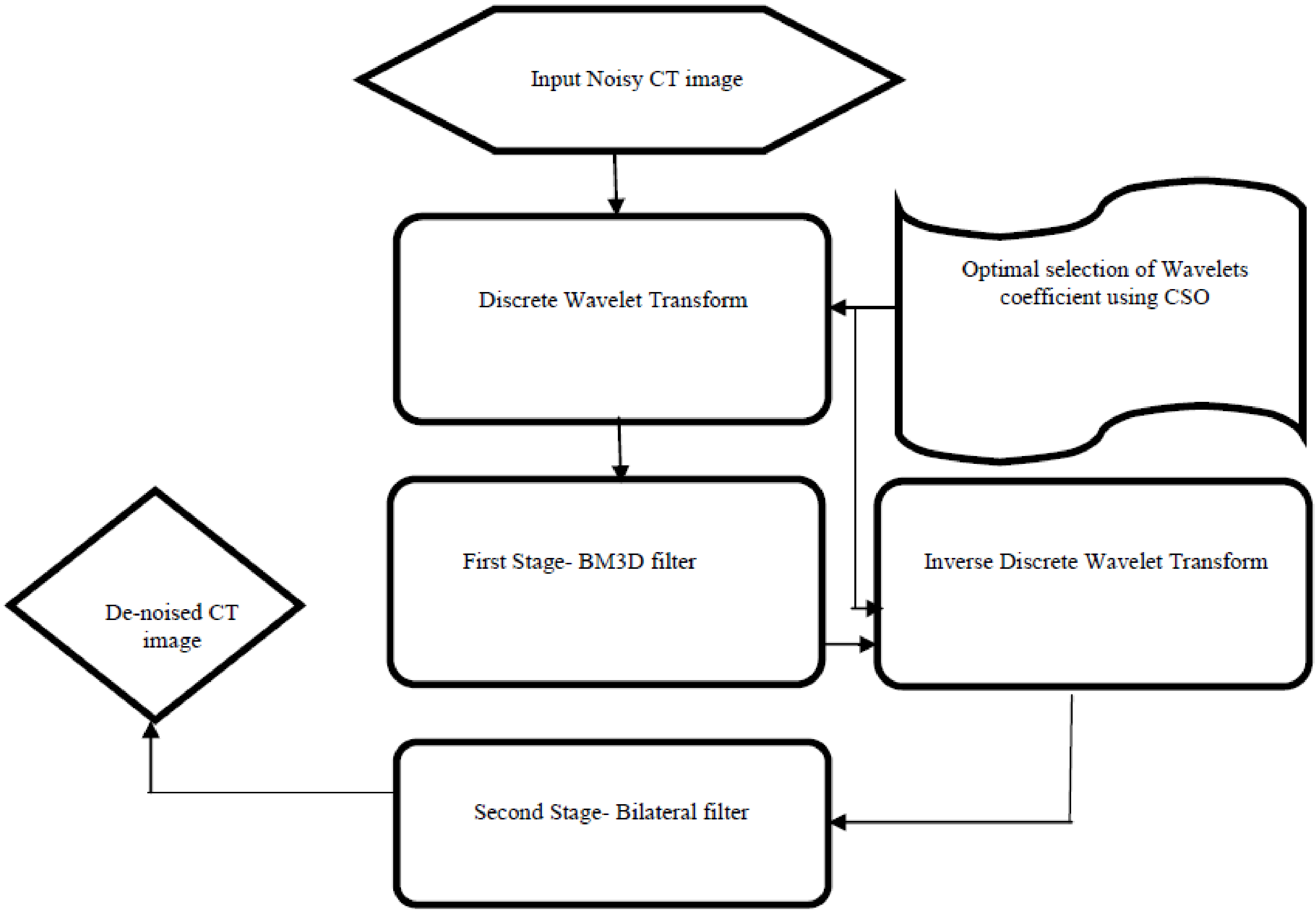


Fig. 1. Overall Architecture of Proposed Method.

B. *First Stage Noise Removal using BM3D Filtering Algorithm*

After image de-composition, BM3D procedure is used to eliminate the noisy contents present in image. BM3D filtering algorithm is mainly applied to LH, HL and HH frequency subdivision bands of DWT image outputs. The BM3D algorithm is divided into two fundamental step ladders. In the initial stage the main focus is on producing essential image estimation and it's widely less noise than the noisy image. In the second stage the fundamental estimate is utilized as a block matching base for pragmatic wiener filtering. The second step could be empirically confirmed to get better quality of an image compared with the initial stage of output.

The principal step is termed as basic estimation, which emphases on eliminating noise present in the image. This step consists of three phases namely, Block-matching (BM), Collaborative filtering (CF), and Aggregation:

1) Block Matching (BM): Initially, the image I is converted into a number of blocks size of $a \times a$. Consider the reference block A. Blocks have been a high similarity with the reference block is formed as a group. Then, the blocks are converted into the 3D array. The similarity of the reference block A and other block O are calculated using equation distance function which is given in equation (1).

$$S\left(A_i, O_j\right) = \frac{\left\|A_i - O_j\right\|}{N_1^2} \quad (1)$$

Where A_i represent the 2D array of reference block A, O_j represent the 2D array of similar blocks. After the similarity calculation, blocks are grouped.

2) Collaborative filtering: At present, the most equivalent blocks of reference blocks are recognized and might be gathered to frame a 3D Array S_1 size is $a \times a \times |S_1|$ .After that, every 3D array is converted to a frequency domain using a 1D and 2D intra-block transform. From transferred data the valuable data is placed in the utmost huge coefficients. Therefore it is conceivable towards decreasing the noise through disposing of little coefficients. The procedure of CF can be represented as:

$$C_F = K_{3D}^{-1}\left(R\left(K_{3D}\left(S_1\right)\right)\right) \quad (2)$$

Where C_F denotes the collaborative fitter output, K_{3D} is the 3D linear transform is usually actualized by isolated 2D and 1D linear transformation, R represent the hard thresholding operator, which is used to regulate the transform coefficient. The threshold is calculated using equation 3.

$$R(x) = \begin{cases} 0, & |x| \le \sigma \cdot \chi_{3D} \\ x, & |x| > \sigma . \chi_{3D} \end{cases} \tag{3}$$

Where

χ_{3D} → Hard-thresholding parameter

σ → Standard deviation

Meanwhile, noise is found in the little coefficients and it is feasible to lessen noise and safeguard best subtleties in the images over the hard-thresholding administrator. Simultaneously CF understands the separation of image signal and noise deprived of expending energy.

3) Aggregation: After filtering, overlapped blocks of the image are to be recovered to their unique positions. Then weighted average (WA) measure based images are estimated. In common, the WA is apprehended by conveying suitable weighting components to the groups of blocks and the weight W_ρ can be displayed as:

$$W_\rho = \begin{cases} \frac{1}{N_c}, & N_c \ge 1 \\ x, & N_c < 1 \end{cases} \tag{4}$$

Where

N_c → Quantity of the persisted non-zero coefficient

We obtain the small number of non-zero co-efficient implies the number of noise detached using collaborative filter since its weight of the block is superior. The basic estimation of the de-noised block D_{basic} is given in equation (5).

$$D_{basic}(i) = \frac{\Sigma_{Op}\ \Sigma_{Q \in O_p} W_i . R_{PQ}}{\Sigma_{Op}\ \Sigma_{Q \in O_p} W_i . x_Q} \quad \forall i \in I \tag{5}$$

Where

Q → Similar block of the present operational block comprises the pixel i

O_p → Set of entirely available blocks

R_{pQ} → Estimation of the block Q

$$R_{pQ} = \begin{cases} R_{PQ}, & i \in Q \\ 0, & i \notin Q \end{cases} \tag{6}$$

The characteristic function x_Q is symbolized as follows;

$$x_Q = \begin{cases} 1, & i \in Q \\ 0, & i \notin Q \end{cases} \tag{7}$$

4) Final estimation: In this stage, final estimation is done with the help of a wiener filter which is used to improve de-noising performance. Initially, the basic estimation output is given to the input of the block BM. In the BM, two groups arrive which is from a noisy image (TP1) and other one from the basic Estimation (TP2). The attained basic estimation output is the same as the actual image. The final weight is calculated using equation (8).

$$W_{final} = \frac{|K_{3D}(T_{P2})|^2}{|K_{3D}(T_{P2})|^2 + \sigma^2} \tag{8}$$

The final estimation F_{final} is attained using equation (9).

$$E_{final}(i) = \frac{\Sigma_{Op}\ \Sigma_{Q \in Op} W_{final} . R_{PQ}}{\Sigma_{Op} \Sigma_{Q \in Op} W_{final} \cdot x_Q} \quad \forall i \in I \tag{9}$$

Compared with the mutual modest hard-thresholding process, Wiener filtering is more effective and the outcome is more precise.

C. Second Level Noise Removal using the Bilateral Filter

After the initial stage of noise removal, bilateral filter (BF) is applied to the first stage output image to improve the image quality. The BF has established its potential for image de-noises with edge protection related to additional spatial domain filtering. It is a very simple and non-iterative filter. BF is based on domain filtering as well as range filtering.

Let f(x) be the input image the low-pass domain filter is applied to the input as well as the output is given by the condition 10-13,

$$f(z) = k_d^{-1}(z) \iint f(\alpha). e(\alpha, z) d\alpha \tag{10}$$

where, e (α, z) = geometric distance among centre x also close by point α .likewise,range filtering is given in the subsequent equation 11 as,

$$\text{h (z) } k_r^{-1}(\text{z}) \iint f(\alpha). s\big(f(\alpha) f(z)\big) d\alpha \tag{11}$$

Whereas s(f (α)f(z)) = “photometric distance” in the middle of center x and close by points ε.

While the bilateral filter is a mixture of both domains filter as well as range filtering, its production could be characterized as (12).

$$h(z) = k^{-1}(z) \iint f(\alpha). e(\alpha, z). s\big(f(\alpha) f(z)\big) d\alpha \tag{12}$$

At this point, k (z) = normalization constant is defined by the subsequent equation,

$$K(z) = \iint e(\alpha, z) s\big(f(\alpha) f(\alpha) f(z)\big) d\alpha \quad (13)$$

Bilateral filters are mostly utilized to remove noise exactly or precisely. Here first we prefer the window size then we pre-compute the distance weight. Later the bilateral filter is applied to remove noise accurately that is the first step in local region extraction and the next step is intensity value calculation and then the subsequent step calculates the bilateral filter response. Later the de-noised image is obtained.

IV. SIMULATION RESULT

The performance of proposed image de-noising method is analyzed in this section. For experimentation CT images are utilized. The adaptive multi-stage noise removal methodology is implemented in the platform of MATLAB.

A. Data Set Description

The CT lungs images are efficiently occupied in the innovative image segmentation and classification technique that is attained from therapeutic facility just as web sources. The corresponding gathered image dataset have 1000 CT lungs images. Here 750 lungs images acquired from TNMSC kudangulam CT scan center, Tamil Nadu and Marthandam MRI and CT scan center, Tamil Nadu. The remaining images are collected from web resources. Datasets are collected during June 2018- July 2019. It has CT images of females, males and an infant. Fig. 2, 3, and 4 provide some input images.

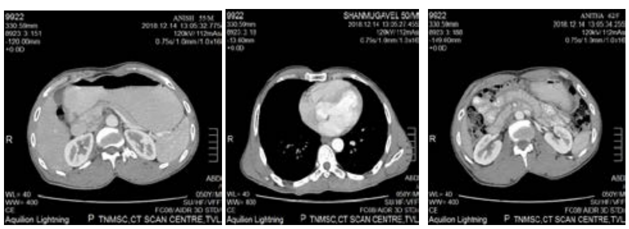


Fig. 2. Sample Images Collected from TNMSC CT Scan Center Tamil Nadu.

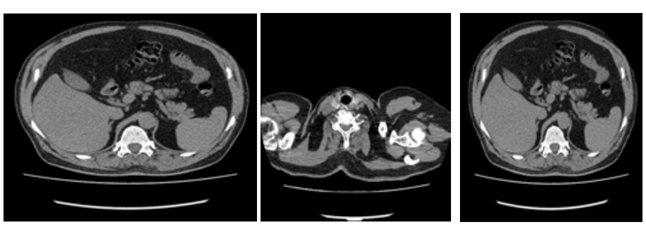


Fig. 3. Sample Images Collected from Marthandam MRI and CT Scan Center Tamil Nadu.

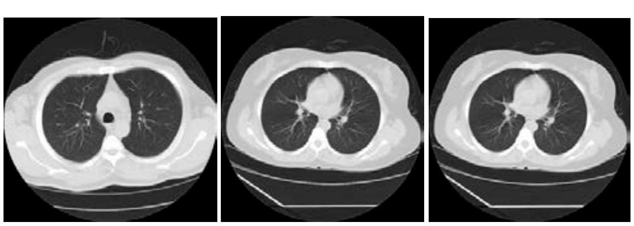


Fig. 4. Experimentally used Sample Images Collected from a Web Source.

B. Evaluation Metrics

The performance of adaptive multi-stage noise removal method is analyzed in terms of various metrics namely peak signal for the noise ratio (PSNR) and Root-Mean-Square error (RMSE), and structural similarity index are explained as below:

1) PSNR: This measure is utilized to measure de-noised image quality. The PSNR is the ratio among the input image and the noise image. Higher PSNR value is given a good quality image.

$$PSNR = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \quad (14)$$

$$MSE = \frac{1}{M * N}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[I(i,j) - I'(i,j)\right]^2 \quad (15)$$

Anywhere;

$I(x,y) \rightarrow$ Input image.

$I'(x,y) \rightarrow$ De-noised image.

2) RMSE: RMSE minimizes the error rates. It serves to summative the magnitudes of the errors in predictions for a variety of times into a solitary measure of predictive power. RMSD is the square root of the mean of the square error. *RMSE Formula* is given by:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \quad (16)$$

3) SSIM: The structural similarity index which is used to measure the comparison among several images. It is a sensitivity based model, that considers the image,

$$\text{SSM}(x,y) = \frac{(2\mu_x 2\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x{}^2 + \mu_y{}^2 + c_1)(\mu_x^2 + \sigma_y^2 + c_2)} \quad (17)$$

Where,

$\mu_x \rightarrow$ Specifies the middling of x,

$\mu_y \rightarrow$ Specifies the middling of y,

$\mu_x^2 \rightarrow$ Specifies the variation of x, σ_y^2 which specifies the variation of y

Experimental results are attained from the adaptive multi-stage noise removal methodology. The following Fig. 5 to Fig. 7 displays the comparative outcomes of existing methodology as well as adaptive multi-stage noise removal methodology for de-noising CT medicinal images.

The principal goal of this article is to perform image de-noising utilizing a blend of BM3M and bilateral filter. Initially the images are decomposed using DWT. To improve the final de-noising performance the coefficient range of DWT is optimally selected with the help of Crow Search Optimisation Algorithm.

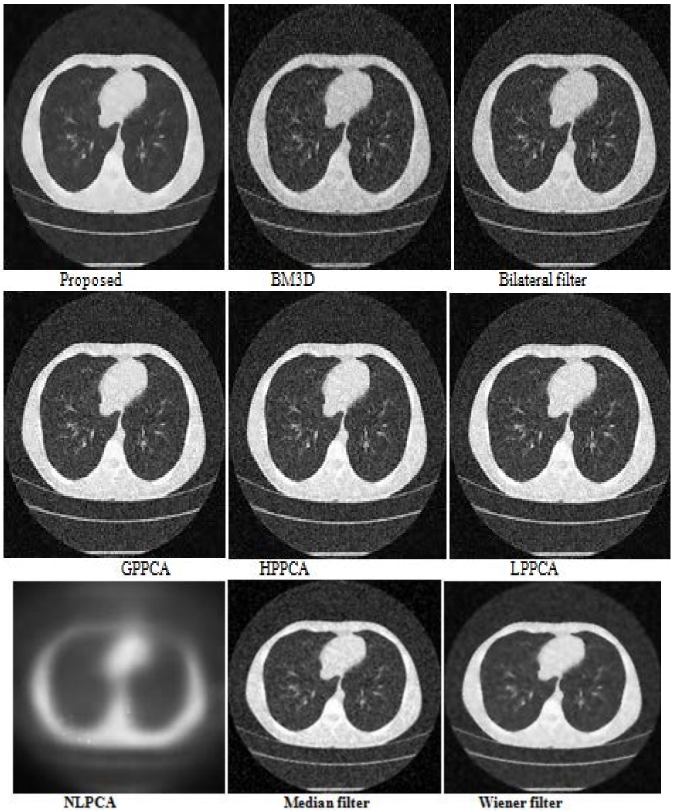


Fig. 5. De-noising Result of Images Collected from Internet Source.

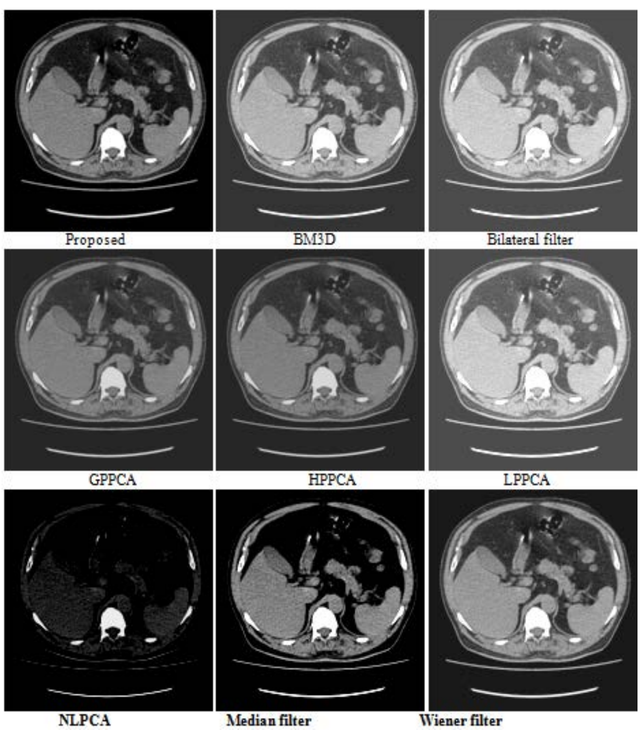


Fig. 6. De-noising Result of Images Collected from Marthandam MRI and CT Scan Center.

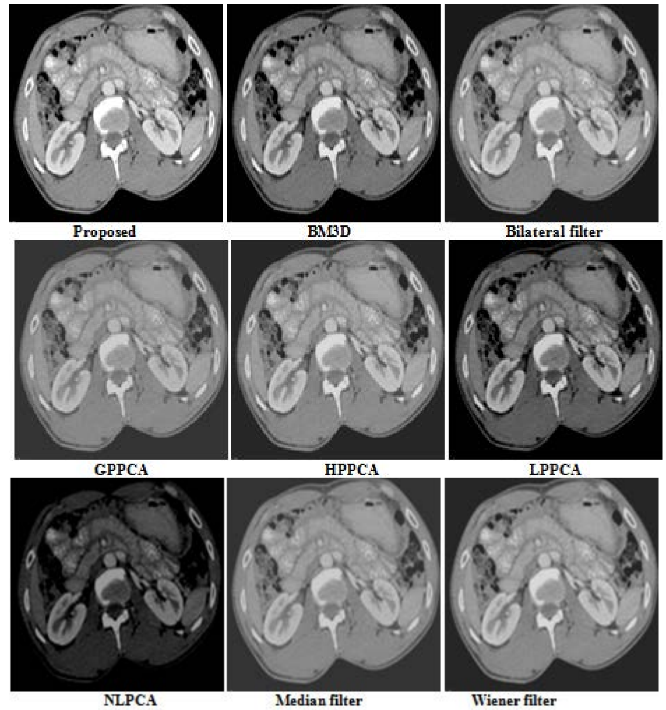


Fig. 7. De-noising Result of Images Collected from the TNMSC CT Scan Center.

Once the optimal coefficients are selected, the BM3D algorithm is applied to the LH, HL and HH frequency bands of DWT image output, and then the bilateral filter is applied to eliminate the noise clearly and to retain the uncorrupted information. In this section, the above Fig. 5 to Fig. 7 shows the comparison results of existing and proposed de-noising CT medicinal images. To evaluate the performance of our adaptive multi-stage noise removal methodology approach, we examine our results with other existing approaches. In this we compare our work with the following existing techniques which is named as BM3D, Bilateral filter, Global Patch Principle Component Analysis (GPPCA), Hierarchical Patch Principle Component Analysis (HPPCA), Local Patch Principle Component Analysis (LPPCA), Non-Linear Principal Component Analysis (NLPCA), Median filter and Wiener filter based image de-noising approaches. Compared to the existing approach our proposed adaptive multi-stage noise removal methodology achieve a better result because of our proposed strategy using the de-noising process in two steps applying BM3D filter the noise is almost removed clearly in the first step and for more exactness and precision bilateral filter is applied, which removes the noise clean and clearly in CT medical images.

Fig. 8 demonstrates the performance analysis of the proposed method using PSNR measure. The maximum PSNR is considered as a good quality image. To demonstrate the efficiency of proposed adaptive multi-stage noise removal methodology based de-noising approach, we compare our algorithm with different algorithm namely BM3D, Bilateral filter, Global Patch Principle Component Analysis (GPPCA), Hierarchical Patch Principle Component Analysis (HPPCA), Local Patch Principle Component Analysis (LPPCA), Non-

Linear Principal Component Analysis (NLPCA), Median filter and Wiener filter based image de-noising.

When analyzing Fig. 8, our algorithm attains the average PSNR of 42.25 db, which is 41.25 db, 41.25, 21.53, 22.32db, 32.025 db, 25.50db, 25.47db and 25.44 db for using BMSD, Bilateral filter, Wiener filter, median filter, NLPCA, GPPCA, HPPCA, and LPPCA respectively. From the PSNR value, we precisely realize our proposed methodology is superior to existing methodology because our proposed scheme prefer optimal co-efficient at the same time it uses filters in two stages in 1st stage BM3D filters are used to remove noise among several CT images. Applying BM3D filter the noise is almost removed clearly in the first step and for more exactness and precision we use bilateral filter to remove noise clearly in CT medical images. Fig. 9 shows a comparative analysis based on RMSE measures. Of these, minimum value of RMSE gives better results of de-noising because the quality of a resultant image is being measured by using RMSE. Comparing to the existing techniques, RMSE measure minimize the error rates of our proposed methodology. When examining Fig. 9 our proposed adaptive multi-stage noise removal methodology achieves the minimum RMSE of 0.7157348629. Here the proposed approach attains maximum SSIM of 0.9110654649, which is highly compared to other existing algorithms. In this, the maximum value of SSIM measure gives better results because SSIM measures the similarity among several images when examining Fig. 10 our proposed adaptive multi-stage noise removal methodology accomplish the utmost SSIM measure of 0.9110654649. From the experimental outcomes, we obviously understand our proposed methodologically gives out enhanced results compared to other existing approaches and the performance comparison is shown in Fig. 11 using mean of PSNR(dB) values. Fig. 12 shows the intensity variation of noise and de-noised CT image. Table I shows the performance of proposed approach by altering noise level. Here, the performance is analyzed based on three level noises like as 0.02, 0.04 and 0.06. When analyzing Table I, after applying noise also our proposed approach attains the excellent PSNR value. This is because of two level filtering approaches. As a result, it is clear to us that our proposed method produced an excellent result compared to other methods. To prove the effectiveness of the proposed methodology, we compare our algorithm with different methods as shown in Table II. In this performance analyze, we compare our proposed method with already published literatures like Dual Tree Complex Wavelet (DTCWT) [22], Curvelet Transform (CT) [22], Harris and DWT [23], Harris Operator and Wavelet Domain Thresholding (RDTDWT) [24], SRTW [25]. When analyzing the above table our proposed method achieves a higher accuracy and higher PSNR of 42.05 because in our work multilevel denoising is performed as well as adaptive bilateral filter is used. Comparing these existing techniques our proposed method achieves a high quality results.

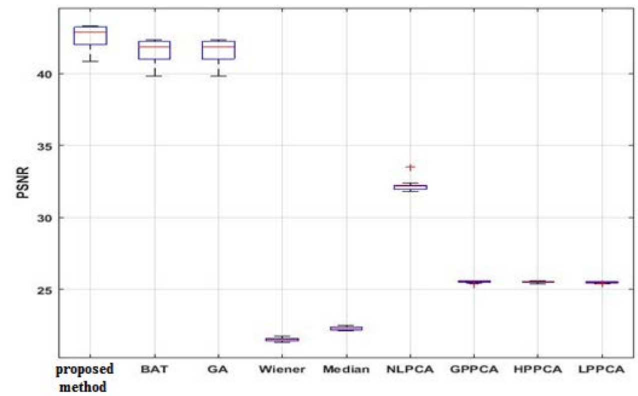


Fig. 8. Comparative Analysis based on PSNR Measure.

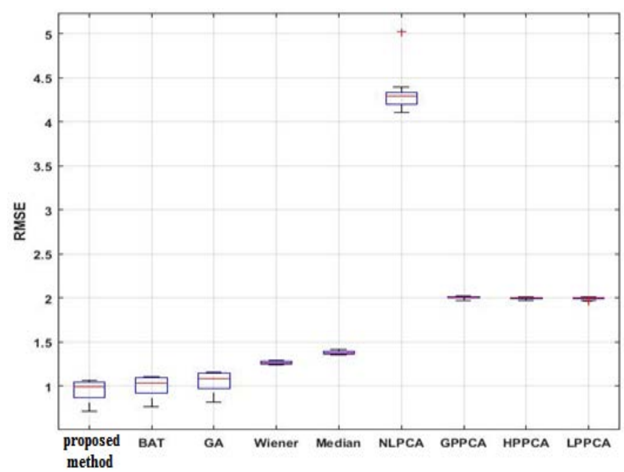


Fig. 9. Correlative Analysis based on RMSE Measures.

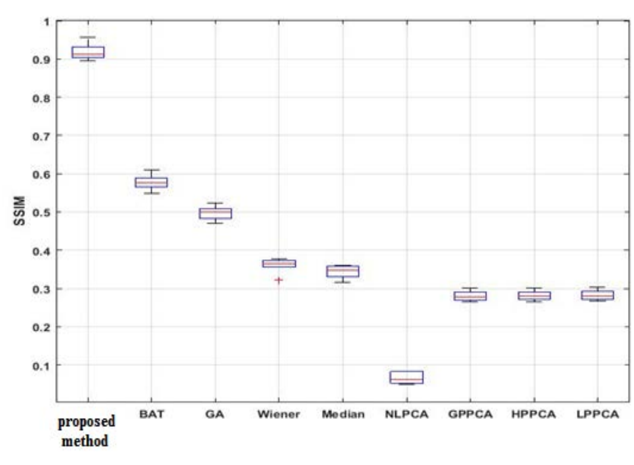


Fig. 10. Comparative Analysis based on SSIM Measures.

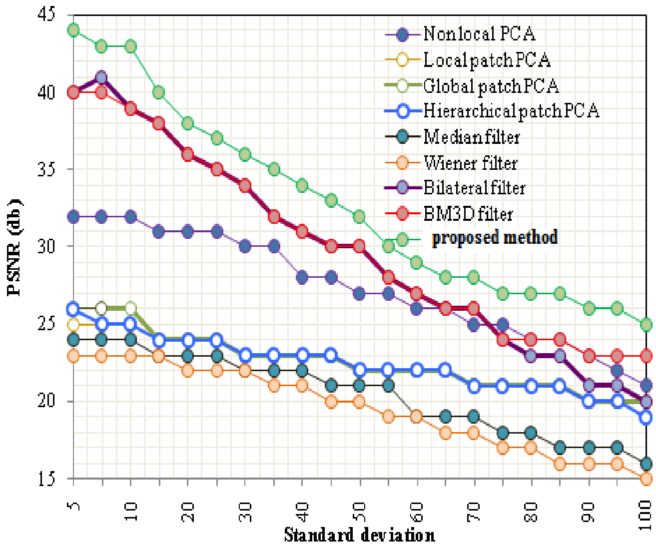


Fig. 11. Performance Comparison by using Mean of PSNR (dB) Values.

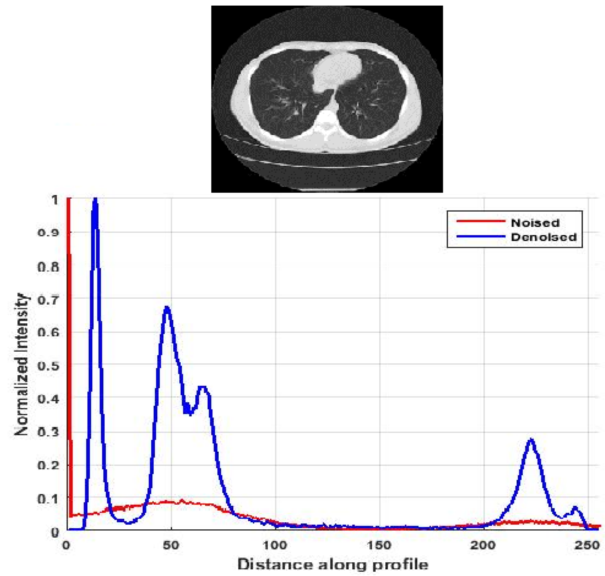


Fig. 12. Intensity Variation for Noised and de-noised Image.

TABLE I. PERFORMANCE EVALUATION USING PSNR MEASURE BY VARYING NOISE LEVEL

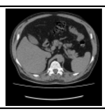
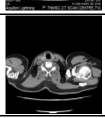
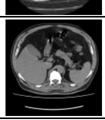
Images	Noise level	BM3D	Bilateral	Wiener	Median	NLPCA	GPPCA	HPPCA	LPPCA	Proposed
	0.02	38.83	38.83	20.55	21.26	30.77	24.58	24.55	24.12	39.83
	0.04	37.11	37.01	19.45	20.42	29.56	23.62	23.02	23.54	38.5
	0.06	35.56	35.23	18.6	19.24	27.10	21.56	22.52	22.32	37.2
	0.02	41.21	41.03	20.24	21.57	30.96	24.32	24.52	24.71	42.03
	0.04	39.67	39.21	19.54	20.63	28.68	23.78	23.02	23.83	41.45
	0.06	38.56	38.02	18.62	19.58	27.57	22.82	21.79	21.83	40.21
	0.02	41.05	39.32	20.48	22.27	31.12	25.41	24.39	25.36	42.05
	0.04	38.21	37.34	19.54	21.54	30.52	24.57	23.47	24.78	41.56
	0.06	37.21	36.33	18.45	20.63	29.47	23.67	22.10	23.02	40.11
	0.02	40.35	40.35	20.51	21.15	31.25	24.37	24.54	24.52	41.34
	0.04	39.47	39.32	19.46	20.64	30.68	23.79	23.89	23.68	40.45
	0.06	38.46	38.21	18.47	19.59	29.68	22.68	22.75	22.68	39.45
	0.02	40.67	40.63	20.61	21.45	30.59	24.69	24.30	24.36	41.21
	0.04	39.56	39.25	19.57	20.68	29.59	23.74	23.85	23.67	40.23
	0.06	38.02	37.95	18.35	19.57	28.51	22.64	22.67	22.65	39.46
	0.02	41.05	39.32	20.48	22.27	31.12	25.41	24.39	25.36	42.05
	0.04	38.21	37.34	19.54	21.54	30.52	24.57	23.47	24.78	41.56
	0.06	37.21	36.33	18.45	20.63	29.47	23.67	22.10	23.02	40.11
	0.02	40.35	40.35	20.51	21.15	31.25	24.37	24.54	24.52	41.34
	0.04	39.47	39.32	19.46	20.64	30.68	23.79	23.89	23.68	40.45
	0.06	38.46	38.21	18.47	19.59	29.68	22.68	22.75	22.68	40.45
	0.02	38.83	38.83	20.55	21.26	30.77	24.58	24.55	24.12	39.83
	0.04	37.11	37.01	19.45	20.42	29.56	23.62	23.02	23.54	38.5
	0.06	35.56	35.23	18.6	19.24	27.10	21.56	22.52	22.32	37.2
	0.02	41.21	41.03	20.24	21.57	30.96	24.32	24.52	24.71	42.03
	0.04	39.67	39.21	19.54	20.63	28.68	23.78	23.02	23.83	41.45
	0.06	38.56	38.02	18.62	19.58	27.57	22.82	21.79	21.83	40.21
	0.02	41.05	39.32	20.48	22.27	31.12	25.41	24.39	25.36	42.05
	0.04	38.21	37.34	19.54	21.54	30.52	24.57	23.47	24.78	41.56
	0.06	37.21	36.33	18.45	20.63	29.47	23.67	22.10	23.02	40.11

TABLE II. PERFORMANCE ANALYSIS IN COMPARISION WITH OTHER ALGORITHMS IN LITERATURE

Methods	**PSNR**
DTCWT	27.9
Curvelet	30.03
Harris&DWT	31.30
RDTDWT	34.45
SRTW	30.93
Proposed Method	42.05

V. CONCLUSION

In our paper, another new innovative image de-noising is proposed using optimal discrete wavelet transform, BM3D as well as the bilateral filter. In our work, the proposed strategy consists of two phases, which are named as discrete wavelet design and image denoising structure.

To improve the delicate regions with higher visual quality the DWT domain transform is applied; where the optimal coefficients are selected using the crow search optimization algorithm. Once the optimal coefficients are selected, the BM3D filtering algorithm is applied to the frequency sub-division bands of DWT image output. At the next stage, the bilateral filter is applied to take away the noise clearly as well as to keep the uncorrupted information well. Experimental results on CT medicinal images are obtainable to estimates presentation of a proposed filter. Our adaptive multi-stage noise removal methodology beat other methodologies based on PSNR, RMSE and SSIM measures.

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