International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-8 Issue-2S, December 2018

Medical Image Quality Enhancement System with Noise Removal Based on NSCT and WOA

J. Jayapal , Ravi Subban

Abstract: ***Noise is one of the inevitable curses of images, which seriously affects the process of image analysis. An image processing can yield better results only when the images are of better quality. Image pre-processing is the most significant phase than any other image processing activities. The main activity of image pre-processing is the image denoising. Though there are numerous denoising systems in the existing literature, the denoising systems for medical images are on high demand due to the sensitiveness. Understanding the requirement, this article intends to present a denoising system for medical images based on the combination of Non-Subsampled Contourlet Transform (NSCT) and Whale Optimization Algorithm (WOA). The performance of the proposed approach is tested in terms of PSNR and SSIM. The proposed approach proves better performance, when compared to the existing approaches.***

Keywords: ***Noise, image denoising, quality enhancement.***

I. INTRODUCTION

Digital images play an integral part of human lives, owing to the increased utilization of digital images in almost all the domains [1]. In spite of the advancement of digital imaging technology, digital images still suffer from the curse of noise. Though there are numerous reasons for the occurrence of noise, the most prominent phases at which noise occur are image acquisition and transmission [2]. The noise is the unwanted information that corrupts quality of a digital image. In certain cases, the presence of noise leads to information loss of an image in addition to quality degradation [3]. This leads to serious effects and affects the performance of the image processing system.

A full-fledged image processing system demands noise-free images, such that the performance of the image processing system can be justified. In order to make the images noise-free, there are numerous techniques available in the literature. Basically, image processing applications are based on five important phases such as image pre-processing [4], segmentation [4], feature extraction [5], classification [5] and post-processing [6]. Image pre-processing is the most significant phase of all image processing activities. The better the digital images are pre-processed, the greater is the performance of the image processing activity. Hence, pre-processing is the basic step of any image processing activity and this phase has a strong impact over the complete functionality of the image processing system. Some of the important processes involved in image pre-processing are image quality enhancement, noise removal, image correction and so on [7]. Quality enhancement intends to improve the quality by adjusting the contrast and brightness with respect to the requirement of the application.

Noise removal is the most popular image pre-processing activity, which paves way for better image analysis. The noise removal algorithms are meant for removing unwanted information from the digital images, such that the image can be analysed effectively [8]. There are different kinds of noises and the techniques that deal with the specific noise type differ from each other. Basically, the denoising approaches can be differentiated into filtering, transformation and statistical based approaches. There are numerous denoising techniques based on these standard approaches.

Though the digital images are exploited by numerous real time approaches, healthcare domain is the most sensitive application, as it is closely related with human lives. Besides this, the presence of noise in the medical images seriously affects the process of diagnosis, which is usually done by the automated Computer Aided Diagnostic (CAD) system [9]. Hence, there is a strong demand for denoising applications in healthcare domain that can ensure better image analytic process. Considering the benefits of denoising algorithms in healthcare domain, this article intends to present an exclusive denoising algorithm for medical images.

This article proposes a denoising algorithm based on transformation by employing Non-Subsampled Contourlet Transform (NSCT) in association with Whale Optimization Algorithm (WOA). Initially, the noisy images are applied with NSCT in different scales and directions. The frequency coefficients of the subbands are chosen by the whale optimization algorithm. By this way, the high frequency parts of the images are removed. Some of the key points of this work are

- This denoising approach can work in multi-scale and multi-directional pattern, which makes it effective in detailed analysis of the medical images.
- As the high frequency parts of an image are detected by optimization algorithm, the images are denoised without any hassles.
- The performance of this approach is found to be satisfactory in terms of PSNR, FSIM and FOM.

Manuscript published on 30 December 2018.
* Correspondence Author (s)
J. Jayapal, Research Scholar, Bharathiar University, Coimbatore, Tamil nadu, India, jayapal.bu@gmail.com
Dr. Ravi Subban, Asst.Prof, Department of Computer Science and Engineering, Pondicherry University, Pondicherry, India

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

The rest of the paper is organized as follows. Section 2 reviews the related literature with respect to image denoising. The proposed approach is elaborated in section 3 and the performance of the proposed work is analysed in section 4. Section 5 concludes the paper with the summary of the findings.

II. REVIEW OF LITERATURE

This section discusses about the related literature with respect to image denoising performed in the transformation domain.

In [10], a technique to denoise color images based on discriminate iterative shrinkage is proposed. The Discriminative Learned Iterative Shrinkage (DLIS) is based on wavelet shrinkage and is carried out by executing shrinkage for all the image patches. The shrinkage function is trained such that it can differentiate between the noisy and noise-free images. This work deals with different noise types in the chrominance channels.

An insulator infrared image denoising approach is presented in [11], which is based on wavelet generic Gaussian distribution and MAP estimation. This work employs Generalized Gaussian Distribution (GGD) as the probability density function by considering the sharp peak and the tail features of the wavelet coefficients. The denoised signal is obtained from the posterior probability density function through the maximum posterior probability estimation.

In [12], the speckle noise is removed from the ultrasound images by exploiting directionally decimated wavelet packets. A double filter bank structure is utilized that is based on the discrete wavelet packet transform and directional filter bank in association with the fuzzy based clustering technique. The speckle noise in the images is removed by means of fuzzy based clustering technique.

An improved denoising method meant for sensor noise based on poisson mixture modelling is proposed in [13]. This work attempts to denoise the image by preserving the texture and edge information of the image by means of a mixture of poisson denoising method. A fast translation based invariant multiscale image denoising scheme is presented in [14]. This approach handles Gaussian and poisson noise by employing translation invariant model.

A hyperbolic wavelet-fisz based ultrasound image denoising technique is proposed in [15]. This work applies a hyperbolic wavelet transform upon an image followed by which the multiscale variance stabilization technique is performed by means of FIsz transformation. The hyperbolic wavelets are meant recovering the original image by considering the anisotropic nature of the structural information.

In [16], the Synthetic Radar Aperture (SAR) images are despeckled by means of a pre-processing filter and Discrete Wavelet Transform (DWT). This work applies the Speckle Reducing Anisotropic Diffusion (SRAD) filter over a noisy image, followed by which a logarithmic transformation is applied for converting the residual multiplicative noise to additive noise. The so filtered image is then treated with DWT and the soft thresholding and guided filter are applied to it. Finally, Inverse DWT (IDWT) and an exponential transform is applied for image denoising.

A denoising system for ultrasound images with the combination of speckle and Gaussian noise is presented in [17]. This work employs dual-tree complex wavelet transform to obtain the coefficients of noise and these coefficients are removed. The noise free image is then formed by applying inverse wavelet transform and it is observed that the dual-tree wavelet performs better than the standard wavelet transform.

In [18], wavelet shrinkage operator based image denoising scheme is proposed to handle poisson noise. This work enhances the results attained by Haar frame and wavelet with respect to poisson noise removal through skellam distribution analysis by operating the shrinkage operators to perform image denoising.

In [19], an image denoising algorithm is presented on the basis of superpixel clustering and dictionary learning approach. In [20], an automated Lion Optimization Algorithm (LOA) based denoising approach that employs multiple filters is presented.

Motivated by these existing works, this article intends to remove Gaussian noise from the medical images by detecting the significant frequency coefficients with the help of WOA and the coefficients with greater noise are removed. This work focuses on Gaussian noise, as it usually happens during medical image acquisition. The working principle of the proposed approach is presented in the following section.

III. PROPOSED MEDICAL IMAGE DENOISING SYSTEM

This section elaborates the working principle of the proposed denoising approach in addition to the overview of the work.

A. Overview of the Work

This work attempts to present a denoising system that can deal with Gaussian noise for medical images. Now-a-days due to the advancement of imaging technology, most of the healthcare applications utilize medical images. However, most of the medical images suffer from noise and is unavoidable. Usually, noise gets accumulated in an image during image acquisition and transmission. The images cannot be processed and analysed in a better way, when the image has noise. The overall flow of the work is depicted in figure 1. The presence of noise can be tolerated by insensitive applications, however the sensitive applications like healthcare based applications demand noise-free images for better analysis. It is studied that the medical images are mostly suffer from Gaussian noise and hence, this work intends to deal with the Gaussian noise by employing WOA and NSCT. The WOA is employed to detect the association of significant coefficients with the least significant coefficients, such that the least significant coefficients are removed. Finally,

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

the images are reconstructed to form noise-free images. The performance of the work is tested and compared against the existing approaches. The following section presents the proposed denoising approach in detail.

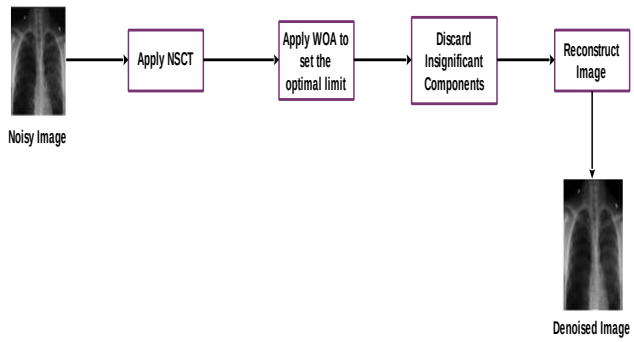

Fig.1. Overall flow of the work

B. Proposed Denoising Approach based on WOA and NSCT

The main concern of denoising algorithms is to preserve the edge information of the images, while removing noise. However it is highly challenging to achieve this goal when better denoising is achieved. This issue is handled by the proposed approach by introducing the combination of NSCT and WOA. The images are then treated by NSCT, such that the coefficients of the noisy image are extracted.

The coefficients with low frequency contain important information and hence, the low frequency coefficients are needed to be segregated from high frequency coefficients. This can be achieved by setting a limit such that the high and low frequency coefficients are differentiated. This task is achieved by WOA and is very important to have an optimal bound, such that the differentiation can be done perfectly and the important information is not missed out by any means. The following section explains the NSCT.

a. NSCT

When the images are subdivided into several image blocks, the NSCT is applied to it. NSCT is based on contourlet transform, where the contourlet transform works on the basis of laplacian pyramid and filter banks with respect to up and downsampling, which makes the contourlet transform shift variant. Though NSCT is based on contourlet, NSCT ensures shift invariance, multiscale and multi-directionality properties. The NSCT works by non-subsampled pyramids and filter banks.

Let IM_x be the input noisy image being passed to the denoising system and the non-subsampled pyramid differentiates the image into low and high pass sub-bands, represented by IM_x^1 and IM_x^0 sub-bands. IM_x^1 and IM_x^0 represents the high and low pass sub-bands respectively by means of the non-sampling filters namely NF_0 and NF_1.

$$IM_x^i = NF_i^* IM_x; \quad i = 0,1 \qquad (1)$$

In the above equation, the convolution operator is represented by $*$. The filter bank of NSCT segregates the high pass sub-bands with respect to multi-directional sub-bands. The outcome of directional NSCT filter bank is represented by A_{pq}.

$$A_{pq} = F_q^t * IM_x^1; where\ q = 1,2,3, \dots, 2^{rx} \qquad (2)$$

In the above equation, 2^{rx} is the count of directional sub-bands at the xth level. This process is repeatedly carried out on the low-pass sub-bands IM_x^0 by fixing $IM_{x+1} = IM_x$. Both the equations (1) and (2) are implemented by the filters maxflat and dmaxflat7, which are meant for performing pyramidal decompositions and the maxflat with order 7 indicates the count of directional sub-bands for a scale, as discussed in [21]. When the images are decomposed by this way, the WOA algorithm is applied for optimal selection of limit or plane for differentiating between the low and high frequency components. The WOA is presented as follows.

b. WOA

WOA is a bio-inspired algorithm that mimics the behaviour of whales [22]. Whales attack a school of fish by encircling them through creating bubbles. The whales attack the fish in two steps, which are termed as exploitation and exploration. The exploitation step encircles the fish and the exploration step intends to look for the fish randomly. The behaviour of whales is represented in the following equations.

$$K = \left|CV_1 . \overrightarrow{A1^*}(i) - \overrightarrow{A1}(i)\right| \qquad (3)$$

$$\overrightarrow{A1}(i+1) = \overrightarrow{A1^*}(i) - \overrightarrow{CV_2} \cdot K \qquad (4)$$

In equations (3) and (4), i implies the current iteration, the attained optimal result is represented by $A1^*$ and $A1$ is the position vector. The operator $\|$ represents the absolute value and $(\cdot)$ is the dot product. The coefficient vectors are represented by CV_1 and CV_2 respectively and are computed by

$$\overrightarrow{CV_2} = 2\overrightarrow{cv_2} \cdot \overrightarrow{rv} - \overrightarrow{cv_2} \qquad (5)$$

$$\overrightarrow{CV_1} = 2 \cdot \overrightarrow{rv} \qquad (6)$$

In equations (5) and (6), $\overrightarrow{cv_2}$ gets reduced with iterations and $\overrightarrow{rv}$ is the random vector produced uniformly within the range of [0,1]. Equation (4) indicates the positional change of the whales and the position of whales is managed by $\overrightarrow{CV_1}$ and $\overrightarrow{CV_2}$ respectively.

The school of fish is encircled by reducing $\overrightarrow{cv_2}$ as indicated in equation 7.

$$cv = 2 - i\frac{2}{Max_i} \qquad (7)$$

In the above equation, i is the total number of iterations and Max_i is the maximum count of iterations. The position of the nearest whale is calculated by considering the distance between the whale x and whale y, as given in equation 8.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

$$\overrightarrow{A1}(i+1) = K' \cdot dis^{cr} \cdot \cos(2\pi r) + \overrightarrow{A1} \times (i) \qquad (8)$$

In equation (8), the distance between the nth whale and the best food source found so far is indicated by $K' = \left|\overrightarrow{A1}^{*}(i) - \overrightarrow{A1}(t)\right|$, c is a constant that represents the shape of the curve and r is the random value from -1 to 1. The food source enclosure and the path determination are represented with a probability (pr) of 0.5, which is presented as follows.

$$\overrightarrow{A1}(i+1) = \begin{cases} Enclosing\ food\ source\ eqn.(4)\ when\ pr < 0.5 \\ path\ determination\ eqn.(8) \quad when\ pr \geq 0.5 \end{cases} \qquad (9)$$

In the above equation, pr is the random value ranging from 0 to 1.

In the exploration step, the whales are selected randomly to look for the source of food. The vector $\overrightarrow{CV_1}$ with random numbers look for the best solution located nearby as represented in the following equations.

$$\vec{K} = \left|\overrightarrow{CV_1}.\overrightarrow{A1_r} - \overrightarrow{A1}\right| \qquad (10)$$

$$\overrightarrow{A1}(i+1) = \overrightarrow{A1_r} - \overrightarrow{CV_2} \cdot \vec{K} \qquad (11)$$

$\overrightarrow{A1_r}$ is the whale being chosen in a random fashion.

This process is repeated until no better solution can be attained further and the best feasible limit is obtained.

Initially, the whales are initialized and deployed in the coefficient matrix of NSCT. Each and every element of the matrix is considered as the food source and the whale chooses the best food source. This process continues until the whales reach the first row of the coefficient matrix. With this operation, the limit can be computed for both the high and the low frequency elements. After detecting the limit, the coefficients with greater frequency are figured out and removed, followed by which an updated coefficient matrix is formed. The image is then reconstructed as follows.

c. Image Reconstruction

Let RF_0 and RF_1 be the reconstruction filters of NF_0 and NF_1 respectively. Let the reconstruction filter of F_q^t is represented by G_q^t. The reconstructed outcome of the image is represented by

$$\widehat{IM}_x = RF_0 * \widehat{IM}_x^0 + RF_1 * \widehat{IM}_x^1 \qquad (12)$$

Where

$$\widehat{IM}_x^0 = \widehat{IM}_{x+1} \qquad (13)$$

$$\widehat{IM}_x^1 = \sum_{q=1}^{2^{rx}} G_q^t * A_{pq}; where\ x = 1,2,\ldots,X \qquad (14)$$

By this way, the noisy image is reconstructed in an iterative fashion and the performance of the proposed approach is evaluated in the following section.

VI. RESULTS AND DISCUSSION

The performance of the proposed denoising approach is evaluated in terms of Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). PSNR is the widely employed qualitative measure for assessing the quality of an image. The SSIM is the standard measure that assesses the quality of image by comparing the similarity between the original and denoised images.

The white Gaussian noise is added to the images in different degrees such as 30, 60 and 90. This work is simulated on Matlab environment in a standalone system with 16 GB RAM. The performance of the proposed approach is compared with the performances of the existing approaches such as hyperbolic wavelet [15], wavelet [11] and curvelet based denoising [23]. Certain sample medical images with white Gaussian noise is considered. The initialization parameters of the algorithm are as follows. The count of whales is fixed between 10 and 20. The PSNR and SSIM are computed as follows.

$$PSNR = 10\log_{10}\left(\frac{255^2}{\sum_{m,n}\left[I_{1(m.n)} - I_{2(m,n)}\right]}\right) \qquad (15)$$

In the above equation, I_1 and I_2 are the original and denoised images. m, n are the rows and columns of the image respectively. The formula to compute SSIM is as follows.

$$SSIM(I_1, I_2) = \frac{(2\mu_{I_1}\mu_{I_2} + c_1)(2\sigma_{I_1 I_2} + c_2)}{(\mu_{I_1}^2 + \mu_{I_2}^2 + c_1)(\sigma_{I_1}^2 + \sigma_{I_2}^2 + c_2)} \qquad (16)$$

In the above equation, $\mu_{I_1}^2, \mu_{I_2}^2$ indicates the mean of original and denoised images. The variance of the original and denoised images is represented by $\sigma_{I_1}, \sigma_{I_2}$. The covariance between the original and denoised images is indicated by $\sigma_{I_1 I_2}$. c_1 and c_2 are constants meant for managing the pixel differentiation. Some of the sample visual results are presented as follows.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

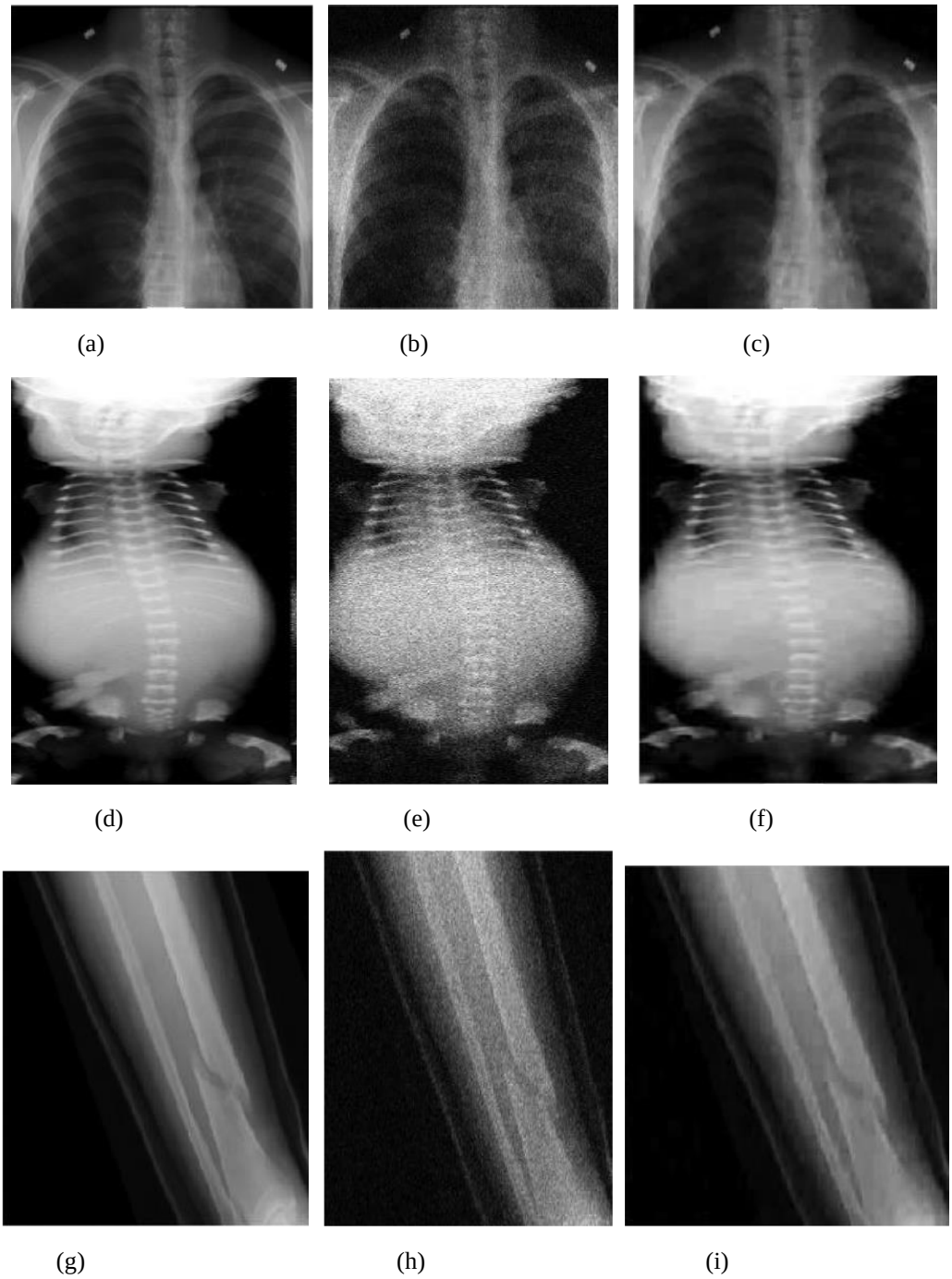

Fig.2. Sample visual results (a,d,g) Input images (b,e,h) Noisy images (c,f,i) Denoised images

From the results, it is observed that the proposed denoising approach shows better performance and the experimental results attained by the proposed approach in comparison with the existing approaches are presented as follows.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

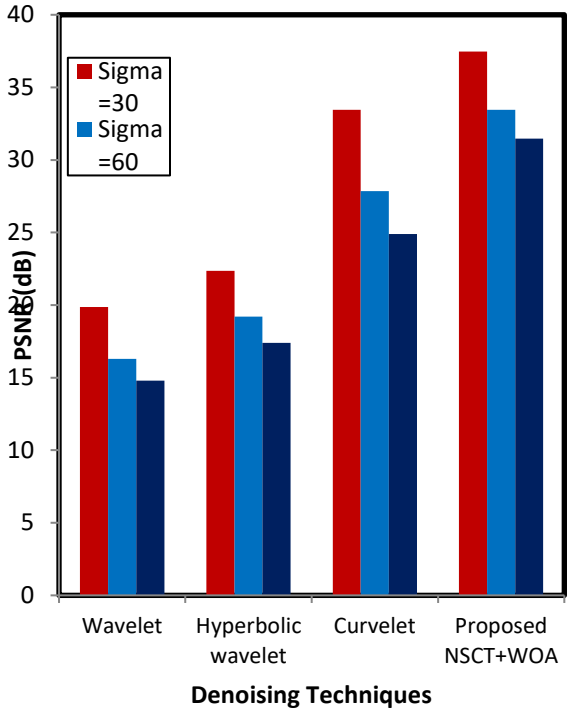

Fig.3 PSNR analysis

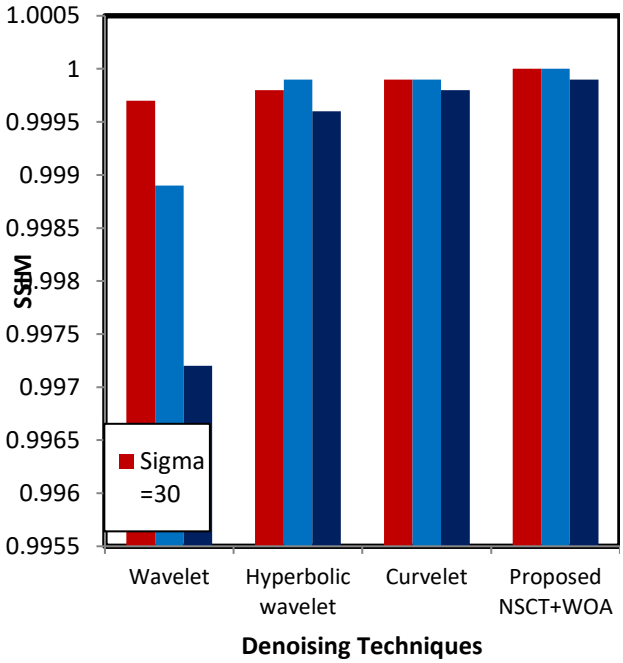

Fig.4. SSIM analysis

From the experimental analysis, the performance of the proposed approach is evident with greater PSNR and SSIM rates. The main reason for the attainment of greater performance scores is the blend of NSCT and WOA. The images are denoised in a better way, while preserving the information of the images. NSCT performs better than wavelet, curvelet and is proven with the image quality. The summary of the work is presented in the following section.

V. CONCLUSIONS

This article presents a denoising approach for medical images based on NSCT and WOA. The basic idea of the work is to differentiate between the high and low frequency components and to preserve the low frequency components, which conceives the significant information of an image. In order to differentiate between the low and frequency parts, an optimal limit is set with the help of WOA. This bio-inspired algorithm helps in differentiating between the high and low frequency parts, through which the images are denoised effectively. The performance of the proposed approach is satisfactory in terms of PSNR and SSIM. In future, this work is planned to be extended to consider some other noises too, as this work is constrained to Gaussian noise alone.

REFERENCES

1. Arivazhagan, Deivalakshmi and Kannan, “Performance Analysis of Image Denoising System for different levels of Wavelet decomposition”, International Journal of Imaging Science and Engineering, Vol.3, 2007
2. Radu Ciprian Bilcu and Markku Vehvilainen, "A NOVEL DECOMPOSITION SCHEME FOR IMAGE DE-NOISING", IEEE International Conference on Acoustics, Speech and Signal Processing, pp.577-580, 2007.
3. Kulkarni, Meher and Nair, "An Algorithm for Image Denoising by Robust Estimator", European Journal of Scientific Research, Vol.39, No.3, pp.372-380, 2010.
4. Bhattacharyya, S. (2011). A brief survey of color image preprocessing and segmentation techniques. Journal of Pattern Recognition Research, 1(1), 120-129.
5. Medjahed, S. A. (2015). A comparative study of feature extraction methods in images classification. International Journal of Image, Graphics and Signal Processing, 7(3), 16.
6. Fellner, F. A. (2016). Introducing cinematic rendering: a novel technique for post-processing medical imaging data. Journal of Biomedical Science and Engineering, 9(03), 170.
7. Hiroyuki Takeda, Sina Farsiu and Peyman Milanfar, “Kernel Regression for Image Processing and Reconstruction”, IEEE Transactions on Image Processing, VOL. 16, NO. 2, Feb 2007.
8. Yong-Hwan Lee and Sang-Burm Rhee, "Wavelet-based Image Denoising with Optimal Filter", International Journal of Information Processing Systems, Vol.1, No.1, 2005
9. Petrick, N., Sahiner, B., Armato, S. G., Bert, A., Correale, L., Delsanto, S., ... & Huo, Z. (2013). Evaluation of computer-aided detection and diagnosis systems. Medical physics, 40(8).
10. Jian Sun ; Zingben Xu, "Color Image Denoising via Discriminatively Learned Iterative Shrinkage", IEEE Transactions on Image Processing, Vol.24, No.11, pp. 4148-4159, 2015.
11. Hongying He ; Wei-Jen Lee ; DianSheng Luo ; Yijia Cao, "Insulator Infrared Image Denoising Method Based on Wavelet Generic Gaussian Distribution and MAP Estimation", IEEE Transactions on Industry Applications, Vol. 53, No.4, pp.3279-3284, 2017.
12. Vimalraj Chinnathambi ; Esakkirajan Sankaralingam ; Veerakumar Thangaraj ; Sreevidya Padma, "Despeckling of ultrasound images using directionally decimated wavelet packets with adaptive clustering", IET Image Processing, Vol.13, No.1, pp. 206-215, 2019.
13. Jiachao Zhang ; Keigo Hirakawa, "Improved Denoising via Poisson Mixture Modeling of Image Sensor Noise", IEEE Transactions on Image Processing, Vol.26, No.4, pp.1565-1578, 2017.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

14. Meng Li ; Subhashis Ghosal, "Fast Translation Invariant Multiscale Image Denoising", IEEE Transactions on Image Processing, Vol.24, No.12, pp.4876-4887, 2015.
15. Younes Farouj ; Jean-Marc Freyermuth ; Laurent Navarro ; Marianne Clausel ; Philippe Delachartre, "Hyperbolic Wavelet-Fisz Denoising for a Model Arising in Ultrasound Imaging", IEEE Transactions on Computational Imaging, Vol.3, No.1, pp.1-10, 2017.
16. Hyunho Choi ; Jechang Jeong, "Despeckling Images Using a Preprocessing Filter and Discrete Wavelet Transform-Based Noise Reduction Techniques", IEEE Sensors Journal, Vol.18, No.8, pp.3131-3139, 2018.
17. Mehdi Mafi ; Solale Tabarestani ; Mercedes Cabrerizo ; Armando Barreto ; Malek Adjouadi, "Denoising of ultrasound images affected by combined speckle and Gaussian noise", IET Image Processing, Vol.12, No.12, pp.2346-2351, 2018.
18. Wu Cheng ; Keigo Hirakawa, "Minimum Risk Wavelet Shrinkage Operator for Poisson Image Denoising", IEEE Transactions on Image Processing, Vol.24, No.5, pp.1660-1671, 2015.
19. J. Jayapal, Dr. S. Ravi, "A Novel Denoising Algorithm Based on Superpixel Clustering and Dictionary Learning Approach", International Journal of Intelligent Engineering and Systems, Vol.11, No.1, pp.142-152, 2017.DoI: 10.22266/ijies2018.0228.15
20. [J. Jayapal, Dr. S. Ravi, "Automated LOA Assisted Denoising Approach with Multiple Filters ", Multimedia Tools and Applications, Under Review, 2018.
21. [Muñoz, J.M.M., de Jes´us Ochoa Domínguez, H., Máynez, L.O., et al.: 'SAR image denoising using the non-subsampled contourlet transform and morphological operators'. 9th Mexican Int. Conf. on Artificial Intelligence, MICAI 2010, Mexico, November 2010, proceedings part 1, pp. 337–347
22. S. Mirjalili , A. Lewis , The whale optimization algorithm, Adv. Eng. Softw. 95 (2016) 51–67.
23. Susant Kumar Panigrahi ; Supratim Gupta ; Prasanna K. Sahu, "Curvelet-based multiscale denoising using non-local means & guided image filter", IET Image Processing, Vol. 12, No.6, pp.909-918, 2018.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)