Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

A Qualitative Approach on De-Noising and Segmentation Algorithms for Melanoma Images

B. Vasantha Lakshmi[1], Dr.K.Sridevi[2]
[1] Gitam University, Visakhapatnam.
[2] Professor EECE, Department, Gitam University, Visakhapatnam

ABSTRACT

This paper presents a novel approach on preprocessing and segmentation algorithms of skin cancer images. Medical image processing involves preprocessing, segmentation, feature extraction & classification, and detection. Preprocessing is first step in image processing applications. Image resizing, de-noising, and hair removal are important stages in preprocessing. In this paper, De-noising of skin cancer images is the first approach and cancerous image segmentation is the second approach. As a process of preprocessing, skin cancer image de-noising is performed using median filter and Wiener filter in filtering method and in transform process, fixed form thresholding algorithm using biorthogonal wavelet (4.4) at 5-level decomposition is implemented. The de-noised images were under segmentation process by edge detection algorithm, sub-band thresholding (LVL_MMC) algorithm, and partitioning in hierarchical tress (SPIHT) using MATLAB 2015. In de-noising, better results are obtained by median filter in terms of the performance metrics like MSE and PSNR, whereas in segmentation algorithms sub-band thresholding algorithm gives better results in terms of minimum number of pixels.

Keywords:
cancerous image, de-noising, median filter, thresholding, wavelet transform.

Introduction

Skin is an outermost tissue and an important body organ, which is a largest organ by its area and weight. It performs several important tasks and acts as a barrier and protecting the body from bacteria, harmful chemicals, and ultra violet radiation from the sun. The area of an adult skin is approximately $16000cm^2$ and about 8% of the body weight. The skin has a complex structure and has two main layers-epidermis and dermis. Epidermis is the outer layer and dermis is the inner layer, these layers consist of many components like cells, fibers, veins, capillaries, nerves, and fine hair furrows. Cancer starts when cells in the body start to grow in an uncontrolled manner. Skin cancer can be classified in to two categories: melanoma and non-melanoma. It is essential to diagnose melanoma at an early stage to reduce the mortality rate. The most common types of non-melanoma skin cancer are basal cell carcinoma, squamous cell carcinoma, and benign, etc. Malignant Melanoma, a deadliest form of skin cancer arises from the uncontrolled melanocytes producing from the epidermis. Melanoma can develop in any part of the body, but more on face, neck, and trunk [13], [14]. The mortality rate can be reduced if we detect the melanoma at an early stage.
This paper is organized as follows: Section II describes the preprocessing of skin cancer images, section III explains methods and metrics used for noise removal(de-noising), image segmentation was discussed in section IV, results in section V followed by conclusion and future scope in section VI.

IMAGE PREPROCESSING

Pre-processing is an important image processing operations performed on acquired image to obtain the better quality image. Skin cancer image enhancement is a crucial procedure to improve the physical appearance of cancerous image, which is first step in preprocessing stage. Image

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

quality can be degraded by imperfection imaging system, poor lightening, and in restoration process. Noise is an unwanted characteristic of an image that can be added at any stage of image acquisition, transmission and also in further processing. Noise can be additive or multiplicative in nature, and effects the intensity values of pixels, which degrades the quality of an image. The corrupted image leads to fault diagnosis. Various types of noise added to the images are salt and pepper noise, poisson noise, speckle noise and Gaussian noise [1],[10]. Hence it is necessary to remove the noise (de-noising) for better quality of image. De-noising is an essential step in preprocessing of skin cancer images. Medical images like ultra sound images troubled with speckle noise, X-ray images with Poisson noise, and dermatological images with impulse (salt and pepper) noise. Salt and pepper noise occurs due to random presence of white and black pixels, (pixels are assigned with maximum or minimum values) which is caused during the transmission of image [2],[6]. In this paper, we de-noise the melanoma skin cancer images from salt and pepper noise (20% noise density) and Gaussian noise (with zero mean, 0.01 variance) by using Wiener filter and median filter in filtering techniques whereas de-noising by soft thresholding algorithm in transform technique.

METHODS AND METRICS FOR DE-NOISING

The standard methods for de-noising skin cancer images are spatial filtering and transform filtering. In spatial domain, we can perform spatial operations on intensity values of input pixels of an image, where as in transform filtering, the filtering process can be done in transform domain (generally frequency domain). In filtering process-Mean filters work well for removing Gaussian noise, median filters can work better for impulse noise, and wavelet transform gives good results in removing impulse noise. Wavelet transform is an extended form of Fourier Transform [1]. De-noising is a process of removing the noise from the cancerous image and preserving the image properties. Filtering methods in spatial domain include median filter, mean filter, wiener filter, where as Transform techniques include Fourier transform, curvelet, and wavelet transforms [11], [15],[16]. In this paper we perform de-noising of cancerous images using median filter, wiener filter in spatial domain where as wavelet transform in transform domain. The performance metrics calculated for the assessment of quality of a de-noised image were MSE, PSNR in filtering methods, and wavelet transform techniques. Wavelet can be implemented as a filter bank that use high pass filter H and low pass filter L. One dimensional signal can be decomposed into some chosen frequency sub bands along the rows of the signal and two dimensional images can be decomposed along the rows and columns in image [17]. Discrete wavelet transform (DWT) is a class of transformation kernel depends on nature of the kernels. The kernels can be represented as horizontal, vertical and diagonal components and is represented as $\psi_H(x,y)=\psi(x)\varphi(y)$; $\psi_V(x,y)= \psi(y)\varphi(x)$; $\psi_D(x,y)= \psi(x)\ \psi(y)$ respectively. An image is a two-dimensional signal, and it can be represented as x(i,j). Each row is filtered first and then down-sampled to get two images represented by (i,j/2), then every column is filtered and down-sampled to get four sub-bands named as LL, LH, HL, and HH. Hence two-level decomposition requires one 2-D scaling function and three 2-D shifting functions. Wavelet transforms are classified as Haar wavelet, Daubechies wavelet, Bi-orthogonal wavelet, symlet, etc. Haar wavelet is the simplest one among the wavelet family. The Haar wavelet decomposes the discrete signal into two sub-signals of equal length. One sub-signal is used to calculate the average and the other one for calculating the difference.Daubechies wavelet has set of scaling function which is orthogonal or orthonormal. This wavelet has finite fading moments. Daubechies wavelets are more effective in frequency response and lesser in phase response. Bi-

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

orthogonal wavelet transform has been broadly used in the fields of image de-noising. It is usually realized by linear phase filters. Bi-orthogonal wavelet transform composed of decomposition and reconstruction filters. One low pass filter (h_n) and high pass filter (g_n) used for decomposition, and one low pass filter ($\tilde{h}_n$) and high pass filter ($\tilde{g}_n$) for reconstruction [4],[15]. The wavelet transform uses the image coding property that, most of the energy is concentrated on the transform components.

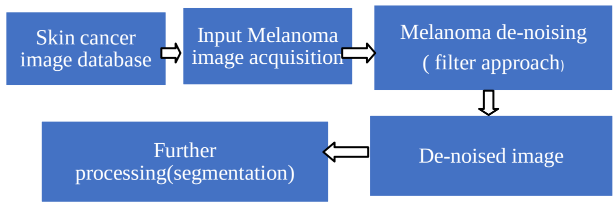


Figure1. Block diagram of the proposed method

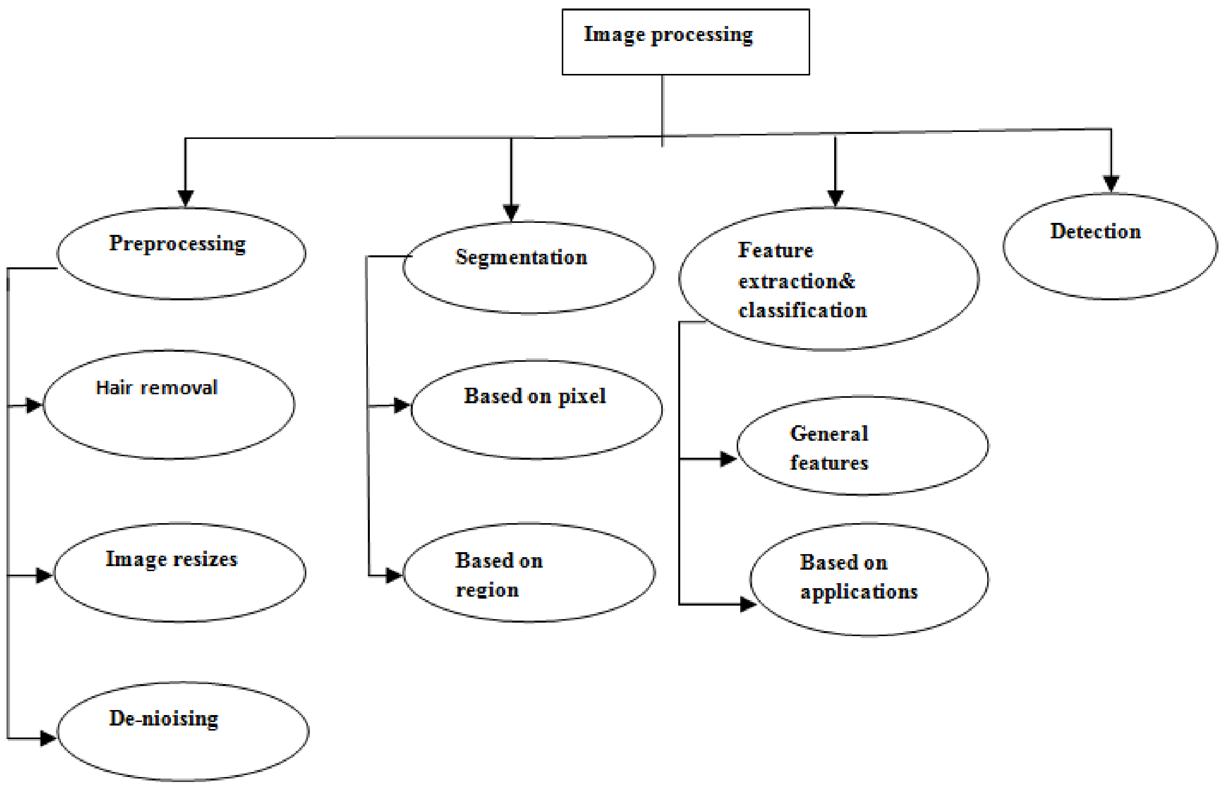


Figure2. Simple block diagram of image processing steps

Mean square error= $\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\{f(x_i,y_j)-f^\wedge(x_i,y_j)\}^2}{I\times J}$ (1)

Peak signal to noise ratio = $20\log_{10}\frac{255}{MSE^2}$ (2)

Mean square error, peak signal to noise ratio are the objective performance metrics used in image de-noising process and evaluated by using above equations (1) and (2) respectively.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

IMAGE SEGMENTATION

Image segmentation is a process of dividing an image into several small regions, and extracting desired information (region) for further processing. The small meaningful region is called region of interest (ROI). There is no unique segmentation algorithm for image segmentation. Image segmentation algorithms are developed based on similarity or discontinuity of pixel intensity levels. Region based segmentation or global segmentation comes into farmer category and segmentation based on points, lines, and edges come under the later one. K-means clustering algorithm was modified to connect the unconnected pixels and mentioned as Simple Linear Iterative Clustering (SLIC) algorithm by Diego Patino and John in [7]. Image segmentation is a process of labeling every pixel of an image, so that pixels of the same labels share some properties. The result of image segmentation is a group of segments that cover the complete image. Each pixel in a region have some property like intensity, color, or any other parameter. In Sub-band thresholding algorithm optimal segmentation is possible by minimizing the coding length (no of bits per pixel) of the data. The proposed method is performed on the melanoma skin cancer image by finding the patterns and then compresses any regularity in the image. In the proposed method each segment is described by texture and shape and these parameters are modeled by PDF (probability distribution function) and coding length. The shorter the coding length the smoother the boundary. The main aim of sub-band thresholding algorithm is to obtain minimum number of bits, which smoothen the boundary. In skin cancer image segmentation, detecting the contour is most important task. In the proposed method Huffman coding with five encoding loops are used for finding the contour. Bits per pixel represent the coding length which is used to smoothen the boundary.

$$compression\ ratio = \frac{p_1}{p_2} \qquad (3)$$

$$bit\ rate = \frac{p_2}{p} \qquad (4)$$

Where, p_1 =message size before compression
p_2 =code size after compression
p=total number of pixels in the image.

Mean square error, peak-signal-to-noise ratio, compression ratio, coding length, and maximum error are the performance metrics evaluated in segmentation process. Compression ratio is represented in equation (3) and bit rate is denoted in equation (4). Maximum error is the difference between original image and segmented image. Below algorithm explains the de-noising and segmentation process implemented in wavelet transform.

Step1: Image Acquisition- cancerous image is selected from the source i.e. ISIC data set.
Step 2: Image Resize-size of the image was modified by image extension toolbox.
Step 3: Image conversion- convert color image to gray scale image.
Step 4: Image de-noising- noise is removed from the image
Step 5: Image segmentation- the de-noised image is under segmentation process by proposed methods.

RESULTS

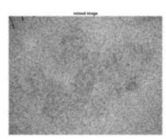
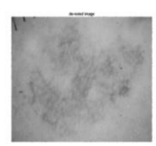
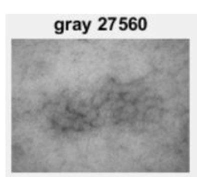
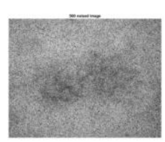
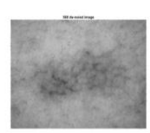
In results we can represent five face images from ISIC data set. Figures in first column shows the original cancerous image , second column represents the converted gray image, third column gives impulse noised image, forth column shows the de-noised image using median filter, and the last column represents the wavelet de-noised image. Table 1 gives the performance metrics,

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

MSE and PSNR of median filter and wiener filter. In segmentation, sub- band thresholding algorithm with Huffman encoding and set partitioning in hierarchical tress algorithm with 5 level Bi-orthogonal wavelet transform was implemented. We tabulate mean square error, peak signal to noise ratio, bits per pixel, maximum error and compression ratio in table2. Wavelet de-noising with soft thrersholding algorithm is given in Figure 3. Figure 4 shows segmentation process with two techniques.

CONCLUSION and FUTURE SCOPE

Melanoma cancerous images are De-noised by using median filter and Wiener filter and observed that median filter performs better than the wiener filter in terms of low value of MSE and high value of PSNR. and soft thersholding algorithm by using biorthogonal wavelet transform performs better than median filter by obtaining minimum MSE (0.49) and maximum PSNR(102.4). In second approach segmentation was performed for de-noised image using edge based algorithms and region based algorithms. In edge based segmentation, Sobel, Prewitt algorithms may not useful in finding the cancerous lesion, canny edge detector works well for these images (Images were not shown in results). Set partitioning in hierarical trees and sub-band thresholding algorithms are implemented in biorthogonal wavelet transform for segmentation of de-noised images. These algorithms are used to sharpen the edges, which gives accurate segmentation of cancerous lesion. Number of bits required for representing the contour. “The lower the number of bits the sharpen the edges”. So, sub-band thresholding algorithm achieves less number of bits thus by sharpen the edges.

 **Figure 3.1(a) ISIC_0024554 original image**	 **Figure 3.1(b) ISIC_0024554gray image**	 **Figure 3.1(c) noisy image**	 **Figure 3.1(d) de-noised image(median filter)**	 **Figure 3.1(e) de-noised image (wavelet transform)**
 **Figure 3.2(a) ISIC_0027560 original image**	 **Figure 3.2(b) ISIC_0027560gray image**	 **Figure 3.2(c) noisy image**	 **Figure 3.2(d) de-noised image(median filter)**	 **Figure 3.2(e) de-noised image (wavelet transform)**

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

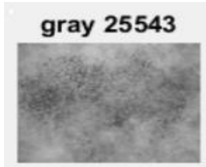
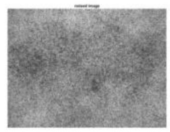
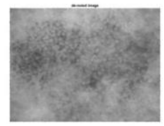
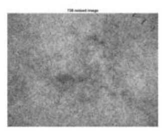
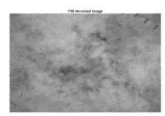
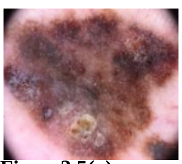
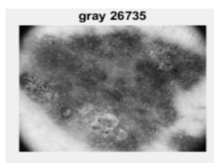
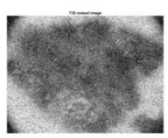
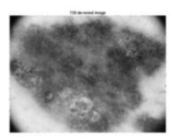
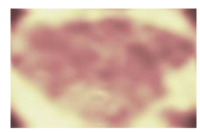
 Figure3. 3(a) ISIC_0025543 original image	 Figure 3.3(b) ISIC_0025543gray image	 Figure 3.3(c) noisy image	 Figure 3.3(d) de-noised image(median filter)	 Figure 3.3(e) de-noised image (wavelet transform)
 Figure 3.4(a) ISIC_0026738 original image	 Figure 3.4(b) ISIC_0026738 gray image	 Figure 3.4(c) noisy image	 Figure3.4(d) de-noised image(median filter)	 Figure 3.4(e) de-noised image (wavelet transform)
 Figure3.5(a) ISIC_0026735original image	 Figure3.5(b) ISIC_0026735original image	 Figure3.5(c) noisy image	 Figure3.5(d) de-noised image(median filter)	 Figure3. 5(e) de-noised image (wavelet transform)

Figure3. Represents the original image, gray image, noisy image, de-noised image by median filter and wavelet transform.

Table 1: Comparison of median filter and Wiener filter, bi-orthogonal wavelet transform in terms of MSE and PSNR.

Image no/perfor mance metric	**Mean square error**			**Peak signal to noise ratio**		
	Median filter	**Wiener filter**	**Bi-orthogonal WT**	**Median filter**	**Wiener filter**	**Bi-orthogonal WT**
ISIC_0024554	7.4	15.9	**1.07**	30.74	24.11	**95.45**

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

ISIC_0026735	8.33	20.17	**5.17**	29.71	22.02	**81.11**
ISIC_0026738	7.53	15.3	**1.05**	30.58	24.41	**95.78**
ISIC_0027560	7.24	19.16	**2.36**	30.92	22.47	**92.13**
ISIC_0025543	7.95	15.3	**0.49**	50.84	24.4	**102.4**

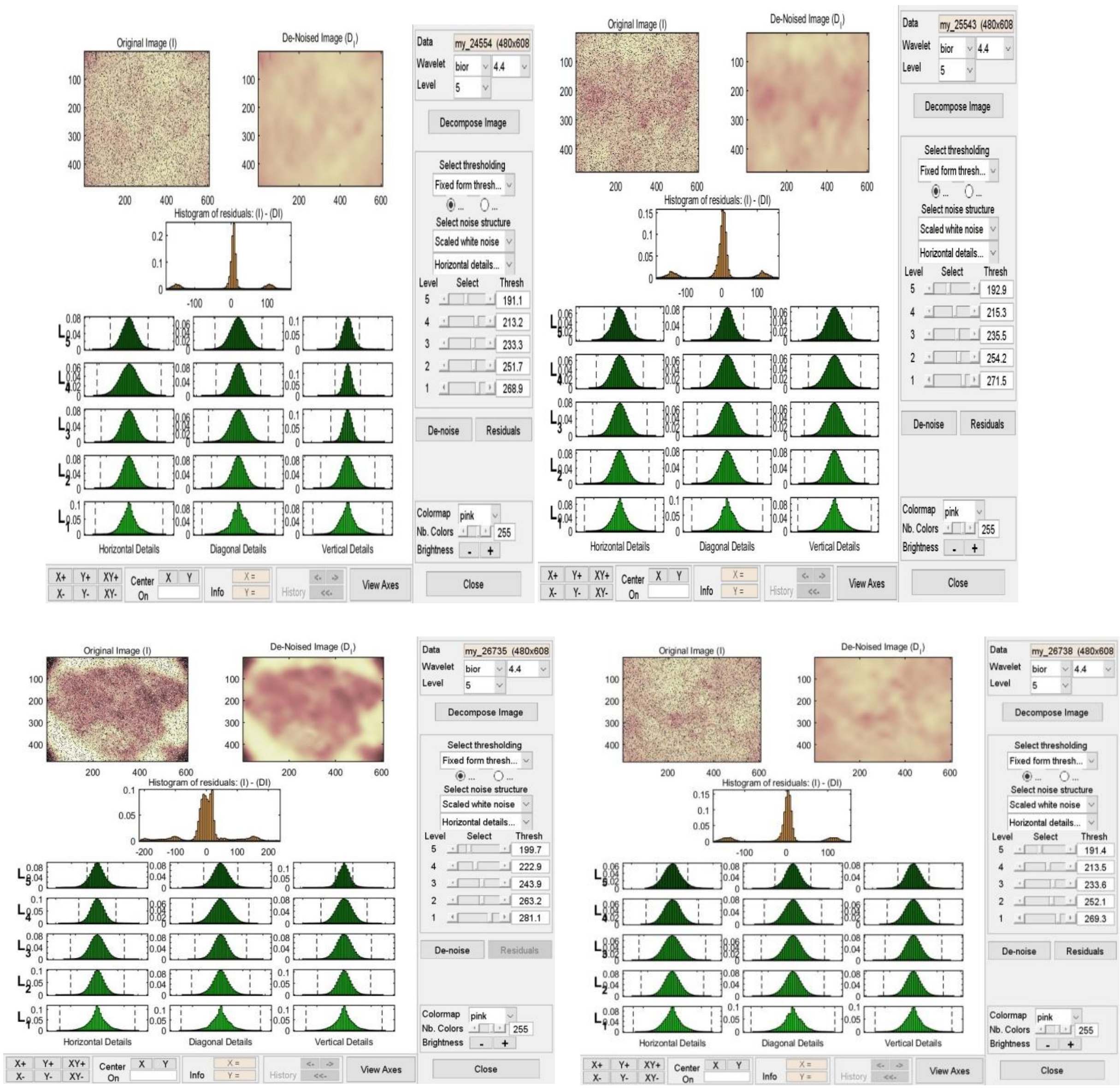


Figure4. Bi-orthogonal wavelet transform de-noised images of 3.1(a), 3.3(a), 3.4(a), and 3.5(a) respectively

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

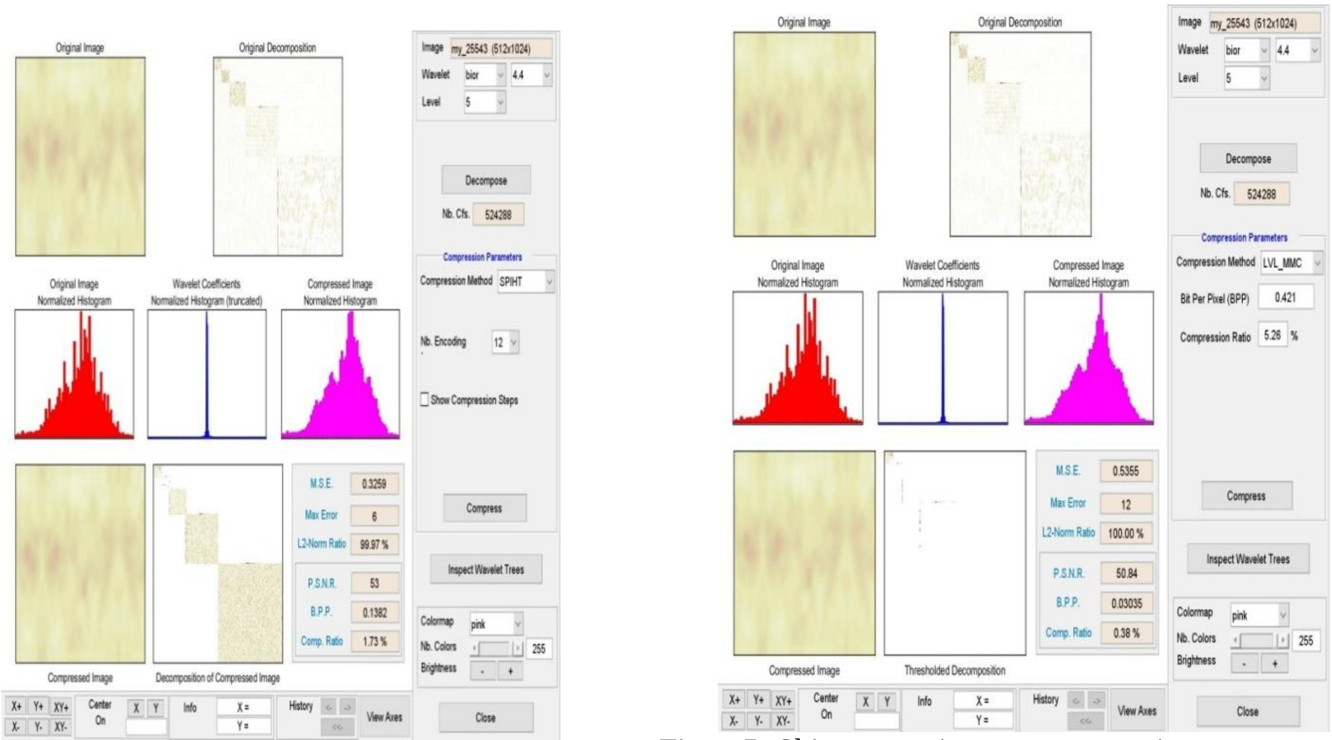


Figure5. Skin cancer image segmentation using set partitioning and sub band thresholding algorithms on an image3.3(e)

Table2. Comparison of Performance metrics of set partitioning and sub band thresholding algorithms:

Image number/ performance metric	Mean square error		Peak signal to noise ratio		Bits per pixel(coding length)		Compression ratio (%)		Maximum error	
	Sub-band thresholding	Set partitioning	Sub-band thresholding	Set partitioning	Sub-band thresholding	Set partitioning	Sub-band thresholding	Set partitioning	Sub-band thresholding	Set partitioning
ISIC_0024554	0.2887	0.3171	53.53	53.12	**0.063141**	0.12328	0.72	0.12328	6	7
ISIC_0026735	0.8658	0.4582	48.76	51.52	**0.049393**	0.12437	0.62	0.12437	18	13
ISIC_0026738	0.5875	0.3375	50.44	52.85	**0.033676**	0.12953	0.42	0.12953	13	6
ISIC_0027560	0.5044	0.3228	51.1	53.04	**0.029770**	0.12621	0.37	0.12621	9	6
ISIC_0025543	0.5355	0.3259	50.84	53.0	**0.033035**	0.1382	0.38	0.1382	12	6

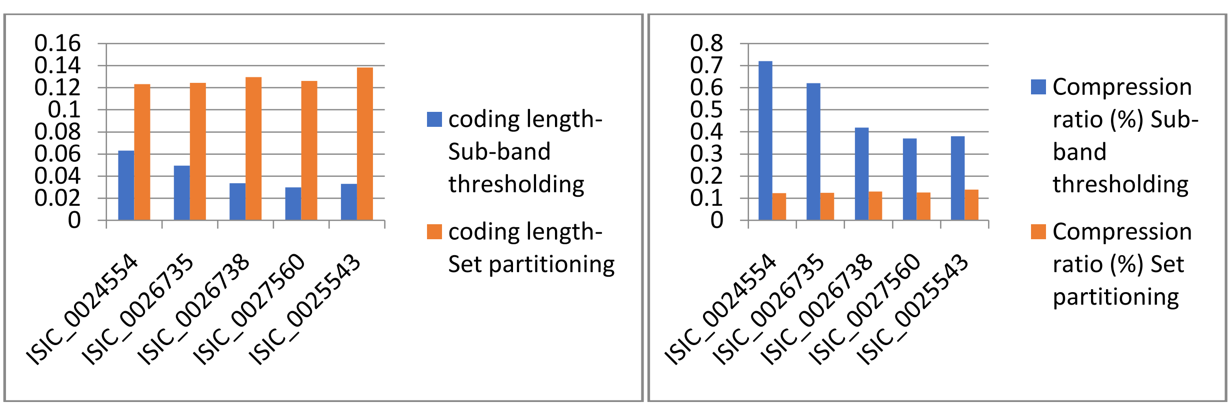


Figure 6(a) and 6(b).Coding length and Compression ratio for proposed algorithms.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

REFERENCES:

[1] Shehzad Khalid, UjmaJamil "Valuable Pre-processing & Segmentation Techniques used in Automated Skin Lesion Detection Systems"17th UKSIM-AMSS International Conference on Modeling and Simulation-2015.

[2] ArshadJavid, W.Y.Chai, Narayan.K, Abdulhammed , Md.SalimJaved, "Automated Segmentation of Brain MR Images by combing Contourlet Transform and K-means clustering Techniques" , Journal of Theoretical and Applied Information Technology 10th August 2013. Vol. 54 No.1 - 2013

[3] Pedro .M. Ferriral Jorge, Teresa Mendonca, M.J,Rozeira, "PH2 - A Dermoscopic Image Database for Rresearch and Benchmarking", Article in Conference proceedings:- Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society, Conference-July 2013

[4] Baochen Jiang, chengyou Wang ,Aiping Yang, Chengyou Wang, ZhengxinHou, "Implementation of Bi orthogonal Wavelet Transform Using Discrete Cosine Sequency Filter", International Journal of Signal Processing, Image Processing and Pattern Recognition, Vol-6, No-4, August-2013.

[5] L.JaafarBelaidi, WalidMourou, "Image Segmentation: A Watershed Transformation Algorithm", Image Anal Sterol -2009,28:93-102

[6] Thakur Kirti, KadamJitendra , Sapkal Ashok, " Poisson Noise Reduction from X-ray images by Region Classification and Response Median Fltering",Sa dhana ,Vol- 42, No- 6, June 2017, pp. 855–863 Indian Academy of Sciences DOI 10.1007/s12046-017-0654-4.

[7] Diego Patino, John .W. Branch, Jonathan Avenda, "Automatic Skin Lesion Segmentation On Dermoscopic Images By The Means Of Superpixel Merging", arXiv:1808.06759v1 [cs.CV] 21 Aug 2018

[8] TR.Thamizhvani, BincyBabu, RJ.Hemalatha, AJR.Dhivya, R. Chandra Sekharan, J.E.Joseph, "Identification of Skin Tumours using Statistical and Histogram Based Features" Journal of Clinical and Diagnostic Research. 2018 Sep, Vol-12(9): LC11-LC15

[9] Cláudio. R. Jung, Jacob Scharcanski, "Sharpening Dermatological Color Images in the Wavelet Domain", IEEE journal of Selected Topics in Signal Processing, Vo-3, No.1, February-2009.

[10] AzadehNooriHoshyar, R. Sulaiman, Adel Al- Jumaily, "Review On Automatic Early Skin Cancer Detection", 978-1-4244-9763-8/11/©2011 IEEE

[11] A. George, K. Manikandan, S. Logesh Kumar, , C. Vijayalakshmi , V. Renuka, "Medical Image De-noising Using Wavelet Transform", International Journal of circuit theory and applications, 9(9), 2016, pp. 3945-3949.

[12] Nadir Mustapha, jiang Ping Li, Mohamed Giess, Saeed Ahmed Khan, " Medical Image De-Noising Schemes using Wavelet Transform with Fixed form Thresholding", International Journal of Advanced Computer Science and Applications, Vol-6 No. 10,

Annals of R.S.C.B., ISSN:1583-6258, Vol. 25, Issue 2, 2021, Pages. 1384 - 1393
Received 20 January 2021; Accepted 08 February 2021.

2015.

[13] https://www.cruk.org/cancerhelp

[14] www.cancer.org/cancer/acs-medical-content-and news-staff.html

[15] A. N. Hoshyar, AfsanehNooriHoshyar, A. Al-Jumali, “ The beneficial techniques in prprocessing step of skin cancer detection system comparing”, International conference on Robot PRIDE 2013-2014-Medical and Rehabilitation Robotics and Instrumantation, ConfPRIDE 2013-2014.

[16] Dr.D. Elizabath Rani, B. Vasantha, “Examination of skin Cancer images using wavelet De-noising”, International journal of innovative technology and exploring engineering, ISSN:2278-3075, vol_9, Issue-2S3,December2019.

[17] B.Vasantha Lakshmi, Dr.D.Elizabath Rani, “De-noising of Skin Cancer Images Using Wavelet Thresholding and Analysis of Statistical Performance Metrics”, Journal of emerging Technologies and Innovative Research , May 2019, Volume 6, Issue 5.