

# A Novel Method for Color Image Enhancement Applied to Bio-Medical images

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**Abstract:** -- Anovelapproach for biomedical colour image enhancement method is proposed in this paper by using mathematical analysis of dual tree complex wavelet transform. The doctor requires the enhanced medical images to give better diagnosis. Thecontrast of biomedical colour images can be improved by data directionality of dual tree complex wavelet transform. The reduction in noise can be done by using wavelet coefficient shrinkage. In this paper we reduced noise present in both enhancedand non-enhanced medical colour images. We have taken the tumour image and computed the PSNR and SSIM of both enhanced image and proposed method by applying Gaussian noise, Poisson noise and speckle noise.

**Key words :** dual tree complex wavelet transform, medical images, image enhancement, contrast, denosing.

## I. INTRODUCTION

Image restoration and image enhancement are fundamental processing methods in image processing. The purpose of image restoration technique is to improve the noise corrupted image by prior knowledge about the degraded image. Image enhancement is to give a better image than an original image for specific application [1].In image processing we come across different types of noise affecting an image such as Gaussian noise, Poisson noise, speckle noise, salt and paper noiseetc. [2].Image enhancement finds many applications in biomedical images. It is needed to improve the contrast of images for better perception of images to find the diseases in human body. In this paper we present image enhancement by applying dual tree complex wavelet transform.We come across different types of colour image enhancement techniques such as local adaptivefilters, based on partial differential equations [3], bilateral filtering.We use two types of colour image enhancement techniques such as random spray ratiensex [4] and random spray automatic colour equalization [5]. By using these random spray methods we get the self-noise due to spray sampling approach to scanning pixels. We come across noise exhibited by differentexisted image enhancement techniques. In this paper we remove the noise due to the enhanced and non-enhanced images with the help of dual tree complex wavelet transform. The random spray automatic colour equalization takes the advantage of both random spray

method and automatic colour equalization methods. The RACE can be applied to dual tree complex wavelet transform (DTCWT) .Noise reduction using DTCWT works for all image enhancement techniques. In this paper we applied this method to RACE.

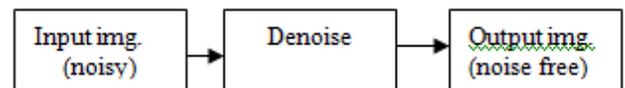


Fig1.flow chart of natural denoising method

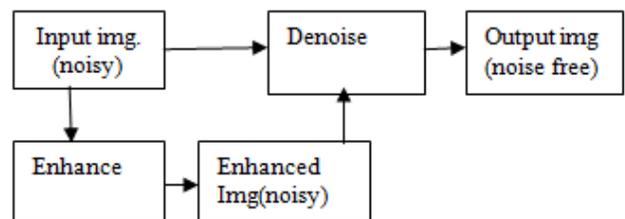


Fig2.flow chart of denoising method

## II. DUAL TREE COMPLEX WAVELET TRANSFORM

Wavelets are one of the most important noise reduction techniques in image processing .Noise reduction using discrete wavelet transform (DWT) is one of the most important technique but it has some drawbacks. One is its not having shift invariance property so that a small change in

input signal causes large change in energy of output wavelet coefficients and another one is poor directional orientation of coefficient. The complex wavelet transform overcomes the drawbacks of DWT. But we are unable to get the perfect reconstruction at the output of filters. In order to improve these properties in single wavelet professor Nick Kingsbury [6] developed the dual tree complex wavelet transform. The DTCWT have the following properties. DTCWT has the nearly shift invariance. The DTCWT having good directional orientation we are having six possible orientations of wavelet coefficients. They are  $\pm 15^\circ$ ,  $\pm 45^\circ$ ,  $\pm 75^\circ$ . Due to this DTCWT find in many applications some of them are texture synthesis and analysis, image segmentation, image sharpening, motion estimation, in satellite images for feature extraction and denoising. In this paper we used the DTCWT for colour image denoising in case of medical images followed by some algorithm. The study of DTCWT is too vast it was explained by selenick[7]. The 2D dual tree complex wavelet transform can be designed with the two different set of wavelet bases. They are given below,

$$\begin{aligned} \psi_{1,1}(x, y) &= \varphi_h(x) \psi_h(y), \quad \psi_{2,1}(x, y) = \varphi_g(x) \psi_g(y), \\ \psi_{1,2}(x, y) &= \psi_h(x) \varphi_h(y), \quad \psi_{2,2}(x, y) = \psi_g(x) \varphi_g(y), \quad (1) \\ \psi_{1,3}(x, y) &= \psi_h(x) \psi_h(y), \quad \psi_{2,3}(x, y) = \psi_g(x) \psi_g(y), \end{aligned}$$

$$\begin{aligned} \psi_{3,1}(x, y) &= \varphi_g(x) \psi_h(y), \quad \psi_{4,1}(x, y) = \varphi_h(x) \psi_g(y), \\ \psi_{3,2}(x, y) &= \psi_g(x) \varphi_h(y), \quad \psi_{4,2}(x, y) = \psi_h(x) \varphi_g(y), \quad (2) \\ \psi_{3,3}(x, y) &= \psi_g(x) \psi_h(y), \quad \psi_{4,3}(x, y) = \psi_h(x) \psi_g(y). \end{aligned}$$

The h and g wavelet filters are related as shown below

$$g_0(n) \approx h_0(n-1), \quad \text{for } j=1 \quad (3)$$

$$g_0(n) \approx h_0(n-0.5), \quad \text{for } j>1 \quad (4)$$

Here j indicates the number of decomposition levels.

### III. RANDOM SPRAY RATINEX (RSR)

The RSR was implemented by using the mathematical analysis of ratinex theory. In this method large no of paths scanning can be eliminated by using random sprays. The 1D paths scanning can be replaced by 2D random sprays. For the computation the formula is remains same in both the RSR and ratinex theory. The operations performed by RSR of spray are used to find the pixel with highest

intensity out of many comparisons. The random sprays can be designed with  $spray_k(i)$  with the point generator. We generated these sprays in the interval  $[0, 2\pi]$  and  $[0, R]$ . Here R is positive real number and this will represent the radius of the spray. The  $RAND_n[0, R]$  and  $RAND_n[0, 2\pi]$  are co-ordinates of image i. Then co-ordinates of generated pixel can be given by

$m = ((m_x, m_y))$  these belonging to the  $spray_k(i)$ .

$$m_x = i_x + \rho \cos(\theta) \quad (5)$$

$$m_y = i_y + \rho \sin(\theta) \quad (6)$$

Here  $\rho \in RAND_n[0, R]$  and  $\theta \in RAND_n[0, 2\pi]$ .  $\delta(r)$  is the mean areolar density vector. Here the locality of spray can be changed by using the function on  $\rho$  as  $\rho(r)$ . In RSR method the co-ordinates can be given by,

$$x = x_i + f(\rho) \cos(\theta) \quad (7)$$

$$y = y_i + f(\rho) \sin(\theta) \quad (8)$$

These are the new co-ordinates of the RSR method. Here we come across different variables. They are R is the radius of the random spray and is selected based on the diagonal of the image because if we select the less value compared to diagonal of image less no of pixels covered for selecting highest intensity pixel it may not cover some pixel without comparisons. If we take value of the pixel larger than diagonal then its computation takes high time without adding advantage of RSR method. So the optimum value of radius will be diagonal of the processed image. We take more no of spray density functions so that it covers all the pixels by adding the result of all spray density function. When random spray ratinex was applied to the images it gives good results in saturation level and colour artifacts will be reduced. In ratinex method if we have large uniform areas they give great amount visible noise. In order to reduce the noise some more extent we go for RACE method.

### IV. RANDOM SPRAY AUTOMATIC COLOUR EQUALIZATION (RACE)

By taking the advantage of both RSR and ACE the Massimo Fierro proposed the new method called RACE image enhancement. The RACE works for both local and global image enhancement methods. The noise occurs in both the cases greatly reduced. The speckle noise occurs in

uniform areas. In order to reduce the noise appearance in output image the image enhancement impact reduced on output image. The elimination of noise was impossible due to the all parameter variations in sprays; such as radius of spray density and spray density functions itself produces the speckle noise. In order to reduce the noise exhibited image enhancement methods and non-enhanced images affected by noise the author Massimo Fierro introduces the new method.

**V. NOISE REDUCTION USING DTCWTCOEFFICIENT SHRINKAGE**

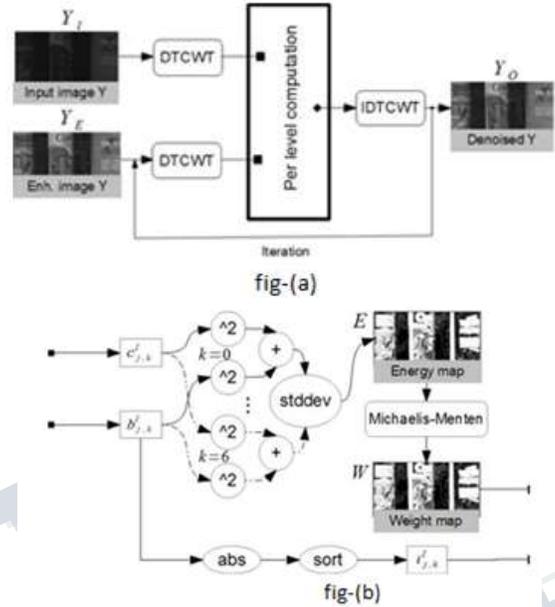
This image enhancement method is based on the directional orientation of DTCWT wavelet coefficients by taking the advantage of data directionality in DTCWT. We transform the image into luma channel. Thereason for selecting luma channel is colour artifacts do not occur. In this image enhancement method we make one assumption that all the input images are taken as either free of noise or contaminated by noise. The shrinkage of wavelet coefficients can be done as follows. The energy computation for all six directions can be computed as sum of squares of both real and complex coefficients. Here  $e_{j,k}$  is the energy of wavelet coefficients. Here  $j$  is the wavelet decomposition level.

$$e_{j,k} = (b_{j,k}^r)^2 + (c_{j,k}^c)^2 \tag{9}$$

Here  $b_{j,k}^r$  is the real wavelet coefficients and  $c_{j,k}^c$  is a complex wavelet coefficient. The energy computed for non-directional data will lead same energy in all directions. But in case of this method we get higher energy in one or two directions of wavelet coefficients remaining all wavelet coefficients have same energy for the given input image. The standard deviation for all six directions of wavelet coefficients can be computed as follows.

$$e_j = stddev_k(e_{j,k}) \tag{10}$$

Here  $k=1,2,3,...,6$  since the coefficients of input image are not normalized.



**Fig3. Proposed method flowchart**

Fig-3. Shows the enhanced images and non-enhanced images are transformed into luma channel using the DTCWT. The output coefficients are transformed into the output image's luma channel via the inverse DTCWT. Fig.3(a) is performed per level of the decomposition. Fig.3(b) shows that the mapping of the weights. These can be obtained by using the Michaelis-Menten function for normalization. All the real co-efficient are obtained in order of magnitude ranking.

For data normalization we apply the Michaelis-Menten function. The data normalization function can be given as below.

$$mm(x, \mu, \gamma) = \frac{x^\gamma}{x^\gamma + \mu^\gamma} \tag{11}$$

Here  $x$  represents quantity to be compressed and  $\mu$  is the estimated data. Here  $\gamma$  is a real valued exponent. Directional sensitivity map of weights can be given by,

$$w_j = mm(e_j, median_k(e_{j,k}), \gamma_j) \tag{12}$$

Here  $\gamma_j$  is called path gain. The value of  $\gamma$  depends on level of  $j$ .

Enhanced image shrinkage coefficients can be given by data directionality. They are given as below

$$b_{j,k}^{\sim E} = w_j \cdot b_{j,k}^E + (1-w_j) \cdot b_{j,k}^I \quad (13)$$

$$c_{j,k}^{\sim E} = w_j \cdot c_{j,k}^E + (1-w_j) \cdot c_{j,k}^I \quad (14)$$

Based on magnitude of directional content of wavelet coefficients of non-enhanced image given the ranks for each of them as follows

$$i_{j,k}^l = ord(b_{j,k}^l), \in \{1,2, \dots, 6\} \quad (15)$$

The output coefficients of this method can be computed as shown below.

$$b_{j,k}^o = \begin{cases} b_{j,k}^{\sim E}, & \text{if } i_{j,k}^l \in \{1,2\} \\ b_{j,k}^I, & \text{if } i_{j,k}^l \in \{3,4,5,6\} \end{cases} \quad (16)$$

$$c_{j,k}^o = \begin{cases} c_{j,k}^{\sim E}, & \text{if } i_{j,k}^l \in \{1,2\} \\ c_{j,k}^I, & \text{if } i_{j,k}^l \in \{3,4,5,6\} \end{cases} \quad (17)$$

The function *ord* returns the all coefficient in the descending order of  $b_{k=1,2,\dots,6}^l$ . The exact meaning of the above equation says that enhanced image gives directional content and shrunk the two most significant coefficients remaining all four coefficient replaced with coefficients of non-enhanced image. These two most significant coefficients are almost not shrunk.

### VI. PROPOSED METHOD

We find many of bio-medical colour images are low contrast and having poor quality. Hence, there is a need to improve the contrast of biomedical images or enhancement of the biomedical images [8]. These enhanced medical images are required for a doctor to know the diagnosis of patients. In order to improve the image quality and contrast. We proposed this method; by using the above dual tree complex wavelet transforms coefficients shrinkage mathematical analysis. We reduced the noise present in images that are already enhanced with our existing image enhancement methods and also remove the noise present in our biomedical non-enhanced images. By using mathematical analysis of DTCWT algorithm when applied to biomedical images we observed improved results. The output results are

compared with the RACE. When compared with the above methods we get improved results.

### VII. RESULTS AND DISCUSSIONS

In this paper, we improved the contrast and image quality of biomedical colour image by reducing the noise present in biomedical images. We compared output image with the RACE image Enhancement method. We compared the PSNR and SSIM for the RACE method and proposed method. We observed that improvement in PSNR and SSIM when compared to the RACE image enhancement methods. In this paper we computed the PSNR and SSIM by applying the tumour image to different types of noise they are Gaussian noise, Poisson noise and speckle noise.

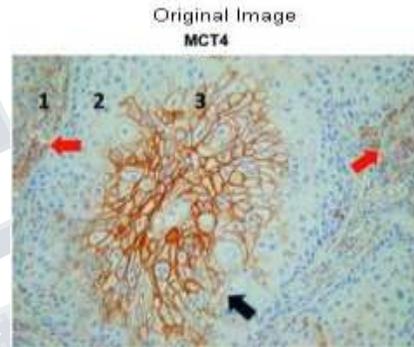


Fig.4 Original tumour image

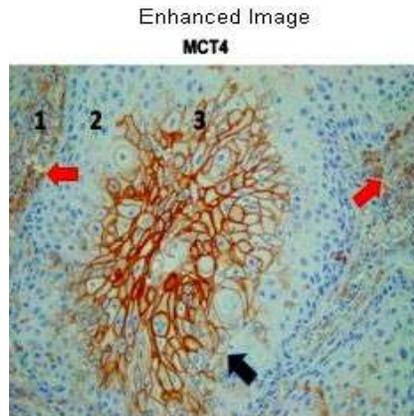
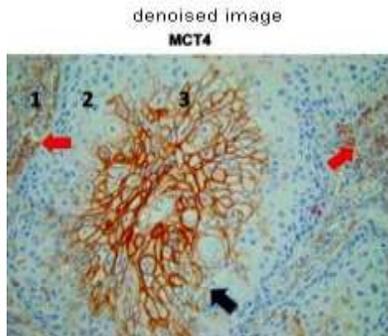
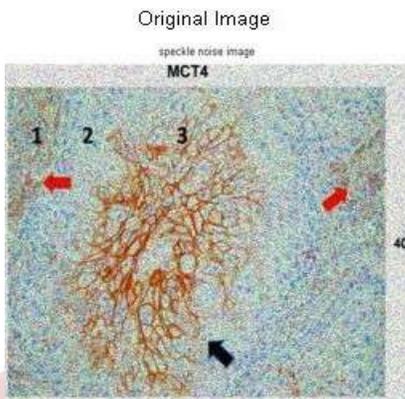


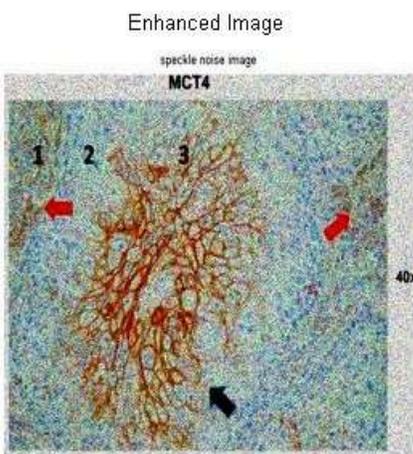
Fig.5 Enhanced tumour image with RACE method.



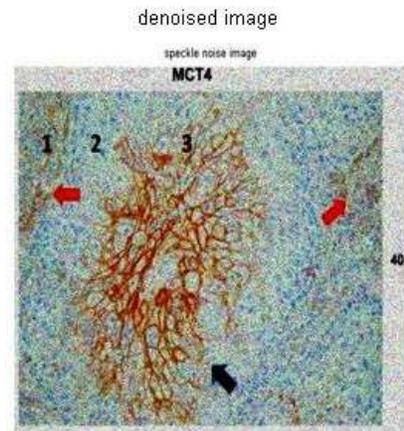
**Fig.6 Denoised tumour image**



**Fig.7 Original tumour image with speckle noise added of variance 0.1**



**Fig.8 Speckle noise added enhanced tumour image with RACE method.**



**Fig.9 Speckle noise added denoised tumour image with Proposed method.**

By observing above figures we can say that proposed method improves the image quality and contrast. We tested the tumour image by adding Gaussian noise, Poisson noise and speckle noise. The computed PSNR and SSIM Tabled as shown in below.

**Table**  
**PSNR ratios and SSIM for tumour image**

Noise type	Img. Name	RACE		Proposed method	
		PSNR	SSIM	PSNR	SSIM
Gaussian	Tumour	38.435	0.9486	39.036	0.9591
		7	1	7	7
Poisson	Tumour	41.217	0.9600	41.931	
		6	9	2	0.9679
Speckle	Tumour	39.790	0.9558	40.597	0.9645
		5	3	3	7

### VIII. CONCLUSION

In this paper, we presented the noise reduction in biomedical colour images. In proposed method the input images are either free of noise or affected by noise. We applied both enhanced images and non-enhanced images as input to the proposed method. This method is possible due to shrinkage of wavelet coefficients. For removing noise present in biomedical colour images we used the DTCWT concept and mathematical analysis of Massimo Fierro. This method presented that in order to remove noise or improve image quality mainly from spray based analysis. The spray based enhanced image applied to proposed method in order to improve image contrast by reducing noise in the enhanced images. For this proposed method we computed both PSNR and SSIM for the taken tumour image by applying Gaussian noise, Poisson noise and speckle noise. In two above cases the results are improved.

### REFERENCES

- 1) Rafael C. Gonzalez, Richard E. Woods, "Digital Image Processing", second edition Pearson.
- 2) V. Vijaya Kishore, Dr. R. V. S. Satyanarayana "Performance Evaluation Of Morphology Based Image Reconstruction Using Different Structuring Elements In The Presence of Noise" International Journal of Engineering Research & Technology IJERTISSN: 2278-0181 Vol. 2 Issue 7, July – 2013.
- 3) Miguel Alemán-Flores, Luis Álvarez-León, "Medical image noise reduction and region contrast enhancement using partial differential equations"
- 4) M. Fierro, W.-J. Kyung, and Y.-H. Ha, "Dual-tree complex wavelet transform based denoising for random spray image enhancement methods," in *Proc. 6th Eur. Conf. Colour Graph., Imag. Vis.*, 2012 pp.194–199.
- 5) E. Provenzi, C. Gatta, M. Fierro, and A. Rizzi, "A spatially variant white-patch and gray-world method for color image enhancement driven by local contrast," vol. 30, no. 10, pp. 1757–1770, 2008.
- 6) N. G. Kingsbury, "The dual-tree complex wavelet transform: A new technique for shift invariance and directional filters," in *Proc. 8th IEEE Digit. Signal Process. Workshop*, Aug. 1998, no. 86, pp. 1–