Volume 6, Issue 11, November 2016 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Medical Image Denoising Using Dual Tree Complex Wavelet Transforms

Deepak, Abhinav Jain
College of Science & Engineering, Jhansi, Uttar Pradesh,
India

Abstract: Medical image enhancement technologies have attracted much attention to improve the quality for better diagnosis. Noise is undesired information which added into medical images which creates the problem to find the diagnoses. From various literatures, it was observed that generally medical images are degraded with Gaussian noise due to mathematical computational errors. It was also analyzed that the radiations to create CT images are harmful for the patients. High radiation dose gives more good quality in terms of noise but these high radiation doses are harmful for the patient. While, low dose CT images are degraded with Gaussian noise. With this motivation, the aim of the paper is to improve the medical image such as CT image quality which is degraded through the Gaussian noise using dual- tree complex wavelet transform. To improve the image quality, noise reduction techniques are used over lower dose images and noise is reduced with preserving all clinically relevant structures. The proposed scheme is tested on various test images and the obtained results show the effectiveness of the proposed scheme.

Keywords: Image denoising; Wavelet transform; Dual-tree complex wavelet transform.

I. INTRODUCTION

Digital image processing plays a key role in medical diagnosis. Medical images are obtained and analyzed to determine the presence or absence of abnormalities such as tumor, which is vital in understanding the type and magnitude of a disease. Unfortunately, medical images are susceptible to impulse noise during acquisition, storage and transmission. Hence, image denoising is a primary precursor for medical image analysis tasks. Conventional smoothening filters and median filters are the most popular filters for noise reduction in digital images. But, a single smoothening or median filter is not enough for completely removing the noise, especially when the noise level is high. Also, it may not preserve image details such as edges during filtering[1-2]. This is a serious issue in medical image analysis because loss of image details results in inaccurate image analysis which may prove fatal to the life of a person. Hence, many methods have been proposed for noise removal from medical images. While some of these methods use complicated formulations, others require deep knowledge about image noise factors. Hence, a simple noise reduction method that removes noise well and preserves image details without relying on image noise factors is desirable [3-5]. Applying a set of denoising and enhancement filters successively on a noisy image may remove noise and preserve image details much more efficiently than a single median or smoothening filter.

Medical image enhancement technologies have attracted much attention since advanced medical equipments were put into use in the medical field. Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc [6-10]. Our targets of medical image enhancement are mainly to solve problems of the high level noise of a medical image. The noise present in the images may appear as additive or multiplicative components and the main purpose of denoising is to remove these noisy components while preserving the important signal as much as possible [11-14]. In medical image enhancement there are many studies, mainly on gray scale transform and frequency domain transform. Frequency domain filtering can be used for periodic noise reduction and removal [15]. We proposed an approach which is used to enhance a medical image by using dual tree complex wavelet transform, by selecting soft and hard thresholding level and thus reducing the noise. In this work, unwanted noisy components can be thresholded without affecting the significant features of the image. We calculate PSNR (Peak Signal to Noise Ratio) and MSE (Mean Square Error) by using these two orthogonal wavelets and then compare the resultants. Image denoising is a procedure in digital image processing aiming at the removal of noise, which may corrupt an image during its acquisition or transmission, while retaining its quality. Medical images obtained from MRI are the most common tool for diagnosis in Medical field. These images are often affected by random noise arising in the image acquisition process. The presence of noise not only produces undesirable visual quality but also lowers the visibility of low contrast objects. Noise removal is essential in medical imaging applications in order to enhance and recover fine details that may be hidden in the data.

With this motivation, this paper has the following structure: section II is about dual-tree complex wavelet transform, section III gives information on the proposed algorithm employed for the denoising process, section IV represents the results and discussion and section V concluded the paper.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

Discrete Wavelet Transform (DWT) has several limitations, Some majors are: aliasing, shift sensitivity and poor directional selectivity [16]. Due to large changes in wavelet coefficients and down sampling, aliasing may occur in DWT. The inverse DWT removes this aliasing only if the wavelet and scaling coefficients are unchanged. Because of shift sensitivity, the small shifts in input signals can cause an unpredictable change in the distribution of energy between DWT coefficients at different scales. DWT cannot distinguish between +45◦ and −45◦ spectral features because of poor directional selectivity. These limitations of DWT can be resolved using complex wavelet transforms (CWT). CWT use analytic filter that decomposes the complex signals into real and imaginary parts in the transform domain. The real and imaginary coefficients are used to compute the amplitude and phase information. To overcome from the limitations of DWT, Kingsbury [16] proposed the dual-tree complex wavelet transform, which allows perfect reconstruction with the advantages of complex wavelets. The dual-tree complex wavelet transform is enhanced version of DWT, with important additional properties: shift invariance and good directionality [17].

III. PROPOSED ARCHITECTURE OF IMAGE DENOISING

With this assumption the medical image is corrupted by Gaussian noise with zero mean and variance as equation (1), the noisy image can be expressed as:

$B(i,j)s = A(i,j)s + \eta(i,j)s$……………………..(1)

Where, $\eta(i,j)s$ is noise coefficient, $A(i,j)s$ is noiseless image and $B(i,j)s$ is noisy image. Noise reduction architecture is proposed as shown in figure 1, where following steps are processed as:

Step 1: Perform dual tree complex wavelet transform (DT-CWT) of medical image corrupted by Gaussian noise to obtain approximation and detail parts.

Step 2: Estimate decomposition level by using log energy.

Step 3: Apply adaptive wavelet based thresholding over the detail parts. Compute the threshold value for each sub-band in all levels. Apply Threshold to all sub-band's coefficients using the optimum linear interpolation threshold function.

Step 4: Perform inverse dual tree complex wavelet transform (Inverse DT-CWT) using step 3.

In the above algorithm, detail part is denoised by thresholding using optimum linear interpolation method. Using modified coefficients, reconstruction is done to get the final denoised image.

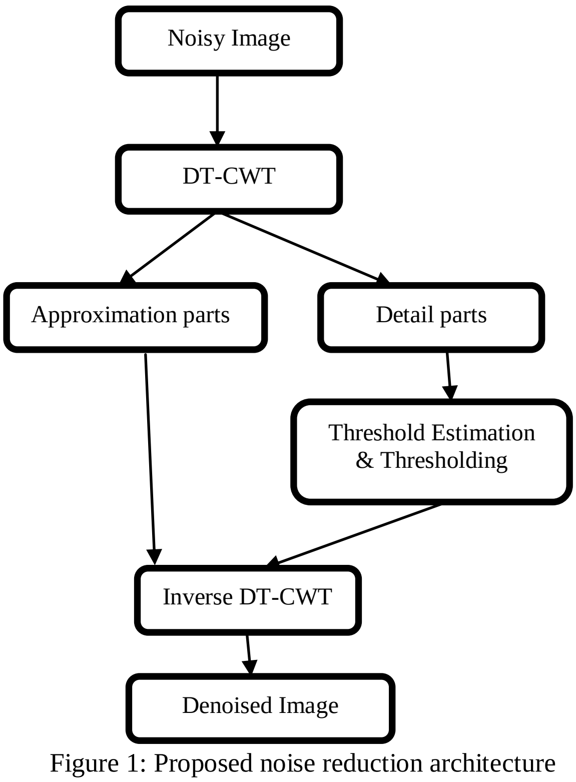

Figure 1: Proposed noise reduction architecture

For CT images, selection of a threshold value is not an easy task. By selecting small threshold value, the result image may be noisy. And for large threshold value, the result image may be blurring. Both are not good for denoising. An optimal threshold algorithm is used for the selection of threshold and used as:

$\lambda(s) = SW\left(\frac{\sigma}{\sigma_{A,s}}\right)]$……………..………… (2)

Where the noise variance can be estimated, as:

$\sigma^2_{\eta_S} = \left[\frac{\text{median } (|B(i,j)_S|)}{0.6745}\right]^2$………………… (3)

Where, $\sigma_{A,s}$is variance of noiseless image for each sub-band and SW represents the weight value for each sub-bands. SW can be calculated by addition of weight value for sub-band of horizontal and vertical direction.

After selecting a threshold value, the process of thresholding is applied by selecting an appropriate algorithm. Hard thresholding and soft thresholding methods are very popular for thresholding. In hard threshold, each coefficient value is compared with threshold value and less than value is replaced by zero. In Soft threshold, replaced by zero process is same as in hard threshold, additionally rest of coefficients are modified by subtracting threshold values. In comparison of both, Soft thresholding gives better performance for visual appearance of images. But soft thresholding has a limitation with large coefficient values.

To overcome those limitations, an optimal linear interpolation (OLI) shrink algorithm is used for thresholding.

$$OL_{\lambda_s}^{(B(i,j)_s)} = \begin{cases} 0, & |B(i,j)_s| \le \lambda_s \\ B(i,j)_s - \left(\frac{\sigma_\eta^2}{\sigma_{B,s}^2}\right)\left(B(i,j)_s, -\mu_s\right), & |B(i,j)_s| > \lambda_s \end{cases} \quad (4)$$

Where, μ_s is the mean value of the sub-band. The above thresholding function is obtained by combining the Shrink technique with the Bayesian MAP estimation.

IV. RESULTS OF EXPERIMENT AND ANALYSIS

The experimental evaluation is performed on CT images with size 512x512. The real CT image dataset is showing in Figure 2 which is found from the public access database (https://eddie.via.cornell.edu/cgi-bin/datac/logon.cgi). Over these images, a Gaussian noise is added to make noisy CT images as shown in figure 3. Further these noisy images are denoised using proposed scheme as shown in figure 5.

To compute the performance of proposed algorithm, we perform a comparison analysis between similar existing schemes and proposed schemes. The existing scheme for comparison is dual tree complex wavelet transform based denoising [16]. The results of dual tree complex wavelet transform based denoising are shown in figure 4. From visual analysis, it can be analyzed that our proposed scheme gives more enhanced results in comparison to existing schemes.

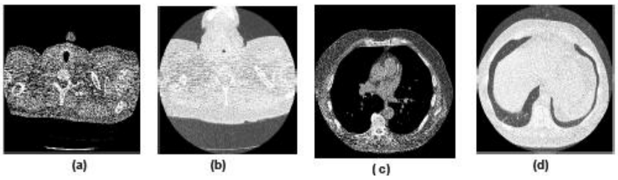

Figure 2: Original CT image data set

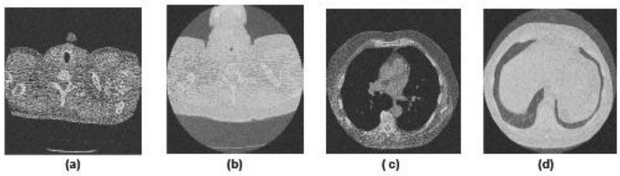

Figure 3: CT image data set (σ =20)

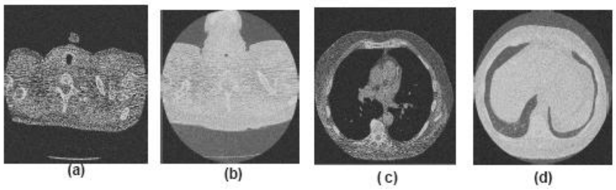

Figure 4: Results of Dual tree based denoisng

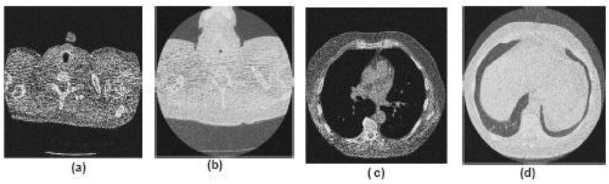

Figure 5: Results of proposed scheme

To measure the performance metrics, between clean and denoised image, the PSNR and Mean error is calculated. The higher PSNR value indicates the best values of the results. However, the Lowest value indicates best values of the results. The mean error can be calculated by the difference mean values of clean and denoised image.

The PSNR can be measured by:

$$PSNR = 10\log_{10}\frac{255^2 mn}{\sum_{j=1}^{m}\sum_{i=1}^{n}[B(i,j)-B(i,j)]^2}\ \text{dB}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

Where m & n are the number of pixels in each column and row, respectively, B(i, j) and B(i, j) are the original and reconstructed images. The PSNR and Mean error (computed from original and denoised images) for synthetic and real medical images are calculated and given in Table 1.

Table 1: PSNR & Mean error

		Dual tree based denoising [16]		Proposed Method	
Medical Image Dataset	Noise (σ_η)	PSNR	Mean error	PSNR	Mean error
CT 1	10	32.35	0.1039	**33.39**	**0.0119**
	20	30.42	0.1103	**31.21**	**0.0573**
	30	28.27	0.1428	**29.76**	**0.0888**
	40	23.36	0.2114	**25.33**	**0.0944**
CT 2	10	32.55	0.1031	**33.51**	**0.0211**
	20	30.41	0.1170	**31.17**	**0.0590**
	30	27.70	0.1537	**28.06**	**0.0737**
	40	22.16	0.2243	**24.62**	**0.0943**
CT 3	10	31.05	0.1003	**32.78**	**0.0233**
	20	29.93	0.1021	**30.30**	**0.0521**
	30	26.87	0.1080	**27.71**	**0.0880**
	40	23.46	0.1629	**25.61**	**0.0929**
CT 4	10	32.15	0.1025	**33.50**	**0.0121**
	20	30.10	0.1294	**31.08**	**0.0393**
	30	27.13	0.1544	**28.31**	**0.0641**
	40	22.97	0.1792	**24.71**	**0.0821**

V. CONCLUSIONS

The proposed method is applied on the basis of thresholding in dual tree complex wavelet transform. PSNR of proposed method is indicating that PSNR decreases with the increasing values of standard deviation of Gaussian noise. Although the computed PSNR values are satisfactory good and the mean error values are very small. Experimental results demonstrate significantly better image visual quality by reducing noise and reserving edges. The PSNR value and mean error indicating better performance of proposed method for additive Gaussian noise in synthetic as well as real medical images. The resultant images are in good quality for clinical diagnosis and may be supported for clinical applications by providing further control over image quality and analysis.

REFERENCES

[1] M. K. Kalra, M. M. Maher and T. L. Toth, “Strategies for CT radiation dose optimization,” Journal of Radiology, vol. 230, no.3, pp. 619-628, 2004.

[2] S. G. Chang, B. Yu and M. Vetterli, “Adaptive wavelet thresholding for image denoising and compression,” IEEE Trans. on Image Proc., vol. 9, no. 9, pp. 1532-1546, 2000.

[3] S. Mallat, “A theory for multiresolution signal decomposition: the wavelet representation,” IEEE Trans. on Pattern Anal. Mach. Intell., vol. 11, pp. 674-693, no. 7, 1989.

[4] M. Nasri and H. Nezamabadi-Pour, “Image denoising in the wavelet domain using a new adaptive thresholding function,” Neurocomputing, vol. 72, nos. 4–6, pp. 1012–1025, 2009.

[5] D. L. Donoho and I. M. Johnstone, “Ideal spatial adaptation via wavelet shrinkage,” Biometrika, vol. 81, no. 3, pp. 425–455, 1994.

[6] Sankur B. and Sezginb M. “Image Thresholding Techniques: a Survey over Categories,” Journal of Electronic Imaging, vol. 13, no. 1, pp. 146-165 2004.

[7] K. Li and R. Zhang, “Multiscale wiener filtering method for low-dose CT images,” IEEE Biomedical Engineering and Informatics, New York pp. 428–431, 2010.

[8] Cheng-Ting Shih, Shu-Jun Chang, Yan-lin Liu and Jay Wu " Noise reduction of low-dose computed tomography using the multi-resolution total variation minimization algorithm, " Proc. SPIE, Physics of Medical Imaging, Vol. 8668, 2013.

[9] A. Borsdorf, S. Kappler and R. Raupach, “Analytic noise propagation for anisotriopic denoising of CT images,” IEEE Nucl Sci Symp Conf Rec, pp. 5335–5338, 2008.

[10] J. Saeedi and M. H. Moradi, “A new wavelet-based fuzzy single and multi-channel image denoising,” Image Vis. Comput., vol. 28, no. 12, pp. 1611–1623, 2010.

[11] L. Shui, Z. F. Zhou, and J. X. Li, “Image denoising algorithm via best wavelet packet base using Wiener cost function,” IET Image Process., vol. 1, no. 3, pp. 311–318, 2007.

[12] Yunhong Li, Xin Yi, Jian Xu and Yuxuan Li, “Wavelet packet denoising algorithm based on correctional wiener filtering,” Journal of Information and Computational Science, vol. 10, no. 9, pp. 2711-2718, 2013.

[13] A. Fathi and A. R. Naghsh-Nilchi, “Efficient image denoising method based on a new adaptive wavelet packet thresholding function,” IEEE Trans Image Process, vol. 21, no. 9, pp. 3981-90, 2012.
[14] A. Buades, B. Coll, J.M. Morel, A review of image denoising algorithms, with a new one, Multiscale Model. Simul. 4 (2005) 490–530.
[15] J.V. Manjon, M. Robles, N.A. Thacker, Multispectral MRI de-noising using nonlocal means, Med. Image Understand. Anal. (MIUA) (2007) 41–46.
[16] Naimi H., Adamou-Mitiche A. B. H., Mitiche, L. 2015 ’Medical image denoising using dual tree complex thresholding wavelet transform and Wiener filter’, Journal of King Saud University- Computer and Information Sciences, Vol. 27, No. 1, pp.40–45.
[17] A. Verma, A. Jain, and B. Kumar. "Dual Tree Complex Wavelet Transform for Image Security using Arnold Method." International Journal of Computer Applications 118.1 (2015).