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Novel Approach For Denoising Of CT Images Using Dual Tree Complex Wavelet Packets And Empirical Mode Decomposition Towards Optimization

A.VELAYUDHAM[1,A *], R.KANTHAVEL[2,B] And K.MADHAN KUMAR[3,C]

[1]Assistant Professor (SG), Department of IT, Cape Institute of Technology, Levengipuram-627114, India

[2]Professor and Head, Dept. of ECE, Velammal Engineering College, Chennai-66, India

[3]Associate Professor, Dept. of ECE, PET Engineering College, Vallioor-627117, India

[a]a.velayudham@gmail.com, [b]r_kanthavel@yahoo.com, [c]madhankn@gmail.com

Abstract: **Computed tomography (CT) images are usually corrupted by several noises from the measurement process complicating the automatic feature extraction and analysis of clinical data. In this research work, we propose a new image denoising technique using Dual Tree Complex Wavelet Packets, Empirical Mode Decomposition and Sobel operator. Here, histon process is used in order to surmount the smoothing filter type and it will not affect the lower dimensions. We have taken into consideration two noises, Gaussian and salt & pepper for the proposed technique. The performance of the proposed image denoising technique is assessed on the five CT images for the parameters, PSNR and SDME. From the obtained outcomes, we can conclude that the proposed denoising technique have shown better values for the SDME of 69.8798 and PSNR of 29.841 for salt & pepper noise which is very superior compared to existing methods.**

Keywords: **CT, EMD, Dual Tree Complex Wavelet Packet (DTCWP), PSNR, SDME**

INTRODUCTION

Denoising of medical images like X-RAY, CT, MRI, PET and SPECT encompass diminutive information about heart, brain, nerves and more which leads physician for precise analysis [13] of diseases. In the case of CT, numerous mathematical and medical applications [11, 12] can be applied to conclude whether the normal tissue has been infected by the mutations of the cancer cell. Recent wavelet thresholding based denoising methods have proved capable, during the conservation of the high frequency signal details [2]. The threshold at certain scale is a constant for all wavelet coefficients in standard wavelet thresholding based noise reduction methods [15]. Fundamentally, the noisy image is transformed into the wavelet domain, then the wavelet coefficients are shifted to soft or hard thresholding, and the result has been inverse-transformed in the final step [16, 17].

The rest of the paper is organized as follows: a brief review of some of the literature works in denoising technique is presented in Section 2. Contribution is discussed in section 3. The proposed CT image denoising technique is detailed in Section 4. The experimental results are provided in Section 5. Finally, the conclusions are summed up in Section 6.

EXISTING APPROACHES

A few of the modern related works concerning the denoising papers are reviewed in this section. Tischenko et al. [1] proposed a structure-saving noise minimizing technique using the correlations between two images for calculation of threshold in the wavelet domain. In addition, Anja Borsdorf et al. [2] by discovering a method to obtain spatially identical input images in case of CT have reduced the problems that occur in this technique. G.Y. Chen and B.Kegl [4] have presented an image denoising method by incorporating the dual-tree complex wavelets into the ordinary ridgelet transform. João M. Sanches et al. [5] have presented a Bayesian denoising algorithm which copes with additive white Gaussian and multiplicative noise described by Poisson and Rayleigh distributions. Faten Ben Arfia et al. [6] have developed a method for image denoising in the filter domain based on the characteristics of the Empirical Mode Decomposition (EMD) and the wavelet technique. Guangming Zhang et al. [7] have developed a model for CT medical image de-noising, which was using independent component analysis and curvelet transform. Syed Amjad Ali et al. [8] have presented an efficient noise reduction technique for CT images using window-based Multi-wavelet transformation and thresholding. G. Landi and E.Loli Piccolomini [9] have modeled a denoising problem in a Bayesian statistical setting by a non-negatively constrained minimization problem.

3. PROPOSED METHOD

The overall diagram of proposed denoising technique is given in Figure 1.

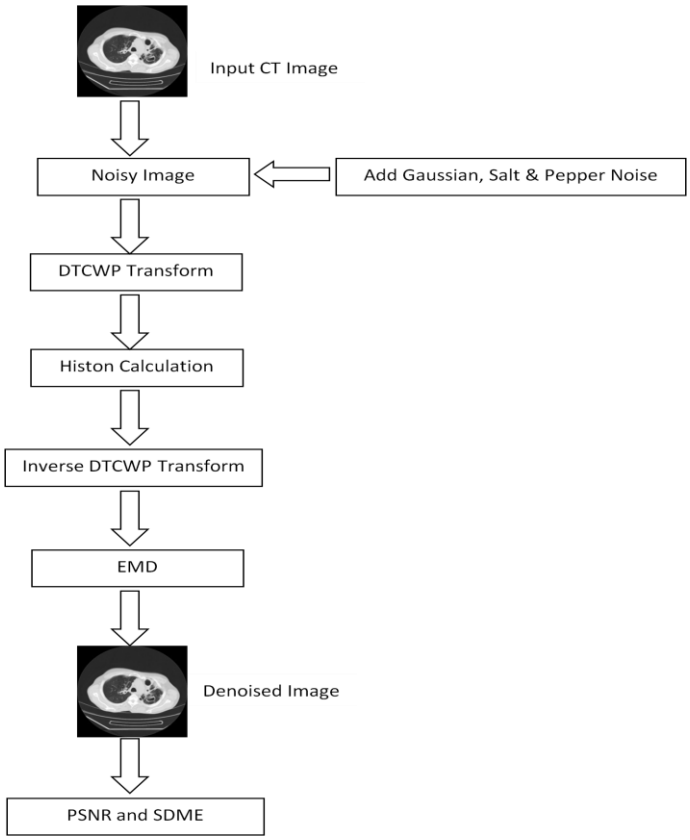


Fig 1: Proposed Denoising Method

The overall proposed denoising process is composed of two phases:

- Noise area identification phase
- Denoising image phase

3.1 Noise Area Identification Phase

Let $'I'(p,q)$ be an original CT image of size $M \times N$. The noises (Gaussian and salt & pepper) are applied on the input CT image, we obtain $N[I(p,q)]$. Where, $N[I(p,q)]$ is the noisy image.

3.1.1 Applying DTCWP

Initially, DTCWP is applied on the noised image $N[I(p,q)]$. Decompose the noise image $N[I(p,q)]$ into four sub-bands, such as HH, LL, HL and LH with the aid of the DTCWPT and we obtain $FW[I(p,q)]$, Where, $FW[I(p,q)]$ is forward DTCWPT output. There are two process involved in the DTCWP transform, such as, forward DTCWPT and inverse DTCWPT. In this step, we have applied forward Dual tree complex wavelet packet.

3.1.2 Applying Histon Calculation

After applying forward DTCWP, the histon calculation is performed. Initially, in the resultant image $FW[I(p,q)]$ by finding the difference between the neighbors and updating the values of neighbors by keeping threshold values, the histon process is carried out. The important steps of histon process are given by:

Using the difference between the nearest neighbors, calculate the pixel value as follows,

$$\text{Difference of a particular pixel} = \text{Nearest neighbor 1} - \text{Nearest neighbor 2} \quad (1)$$

- After finding the pixels values update the pixels values by setting a threshold. Here we used the threshold value as greater than 1 or less than 1.
- Then to find the intensity values of a pixel, we find the difference between the nearest neighbors for the particular pixel values. Using the same formula (1), we find the intensity values of a pixel.
- After finding the intensity values of a pixel, we have to update the values in the image by setting the threshold. The threshold value is greater than or less than 0.5.
- Update the count values in the particular intensity value of a pixel and we check one by one via histogram and plot the values.
- Here, with the difference between the neighbors the intensity values of a pixel is calculated. By keeping threshold, the intensity value of a pixel is calculated. (i.e.) if the calculated difference between the neighbors is greater than one means replace the pixel value with 2 and if the calculated difference between the neighbors is less than one means replace the pixel value with 0.
- The above process repeats until the eligibility criterion occurs. In our process it takes 200 iterations to complete the process. After completing every iteration, the image $FW[I(p,q)]$ is represented as $FW[I(p,q)]', FW[I(p,q)]'', FW[I(p,q)]''',...$ and so on.

By using the above process, we compute and rearrange the pixel values to find the noisy areas without affecting the lower dimensional areas. Thus after completing the rearranging process and having applied inverse DTCWP, we obtain some intensity values of a noisy image $IW[I(p,q)]$. i.e., an inverse DTCWP is then applied to the rest of coefficients to reconstruct the data. Then, the noisy image is given to the empirical mode decomposition process for image enhancement purpose.

3.2 Denoising Phase

3.2.1 Applying EMD

After inverse process, the EMD is applied on the $IW[I(p,q)]$ image. Empirical mode decomposition [3] is an efficient filtering technique to reduce the noise and image smoothing. Firstly, the $IW[I(p,q)]$ image is vectorized and given into EMD. The sifting process begins from the image

$IW(p,q)$ and the initial input to the EMD to the process is followed by

$$input_{mn}(p,q) = IW(p,q) \tag{2}$$

Where m is used as index to show the mth IMF, and m represents iteration number of the current step while (p,q) denotes the spatial image location.

The decomposition process of EMD is as follows:

Calculate all points of local maxima and all points of the local minima of $input_{mn}(p,q) = IW(p,q)$ for every position.

Interpolate the local maxima to form an upper envelope $(e_{\max}(p,q))$.

Interpolate the local minima to form a lower envelope $(e_{\min}(p,q))$.

Calculate the mean of upper and lower envelope for each position

$$(e\_Mean_{mn}(p,q)) = \frac{e_{\max}(p,q) + e_{\min}(p,q)}{2} \tag{3}$$

From the input signal (vector), subtract the mean envelope

$$h_{mn}(p,q) = input_{lk}(p,q) - (e\_mean_{mn}(p,q)) \tag{4}$$

This is a one iteration of the sifting process. The next step is to check if the signal (vector) $h_{mn}(p,q)$ from step (e) is an IMF or not.

Calculate the stopping criterion

$$eps = \frac{\sum_{p=1}^{H}\sum_{q=1}^{W}\left|(e\_mean_{mn}(p,q))\right|}{H \times W} \tag{5}$$

Where, W and H denotes dimensional of the image and eps denotes stopping criterion. Check if envelope mean satisfies the iteration stop criterion for the current IMF. If the stop criterion for the current IMF falls below a small threshold such that $eps < \kappa$, here κ is the small threshold the sifting process is stopped for the current IMF is obtained as $IMF_m(p.q) = h_{mn}(p,q)$. If the stop criterion is not met, the next iteration is started with $input_{m(n+1)}(p,q) = h_{mn}(p,q)$ and this process is repeated from step 1 to find the current IMF.

If the current IMF acquired correctly, the residue signal $R_m(p,q)$ is calculated as $R_m(p,q) = input_{l1}(p,q) - IMF_m(p,q)$ .If the residue does not contain any more extreme points the EMD decomposition process is terminated. Otherwise the next IMF is computed from step (a) using the residue as input, i.e. $input_{(m+1),1}(p,q) = R_m(p,q)$.

The EMD process decomposes the noised image into several IMFs, and final residue R_m. The resultant image is actually sum of these components.

$$IW_{EMD}(p,q) = R_m(p,q) + \sum_{m=1}^{M} IMF_m(p,q) \tag{6}$$

From the equation (6), the image, $IW_{EMD}(p,q)$ is obtained. But, $IW_{EMD}(p,q)$ contains white pixels. For this purpose, we are going to use edge detection technique.

3.2.2 Applying Sobel Operator

In the Sobel edge detection, the convolution mask is slid over the image, manipulating a square of pixels at a time. The edge detected image can be obtained from the Sobel gradient by using a threshold value. If the Sobel gradient values are lesser than the threshold value, then replace it with the threshold value,

If f < threshold value then, f = threshold value (7)

In Sobel edge detector, the region based edge detection process consists of threshold with values less than 5 and hence the values less than or equal to five are removed and then the image splits into two blocks as G_P, G_Q. After splitting the blocks into 8*8, the edge detection process takes place.

The magnitude of the gradient is calculated using the formula as follows,

$$|G| = \sqrt{G_P^2 + G_Q^2} \tag{8}$$

The direction of the gradient is calculated using the formula,

$$\theta = \tan^{-1}\left(\frac{G_Q}{G_P}\right) \tag{9}$$

Where, G is the gradient magnitude

θ is the gradient direction.

G_P And G_Q are the blocks which we split and then the Sobel edge detector process takes place. After finding the magnitude and direction of the gradient in Sobel edge detector the intensity values of a pixel is updated. Here in our proposed technique we find the PSNR and SDME values by calculating the difference between the pixels in the image.

IMPLEMENTATION METHODOLOGY

The proposed approach of image denoising is experimented with the CT medical images and the result is evaluated with the PSNR and SDME.

4.1 SIMULATION ENVIRONMENT

The proposed method is implemented in a Windows machine having a configuration of Intel (R) core I5 processor, 3.20 Ghz, 4 GB RAM and the operation system platform is

Microsoft Windows7 Professional. We have used Matlab latest version (7.12) for this proposed technique.

4.2 Evaluation Metrics

The formulae used to compute the evaluation metrics PSNR and SDME values are given as follows.

4.2.1 Peak Signal to Noise Ratio (PSNR)

The formula for PSNR value computation is,

$$PSNR = 10\log_{10}\frac{E_{\max}^2 \times I_w \times I_h}{\sum\left(I_{xy} - I_{xy}^*\right)}$$

Where, I_w and I_h → Width and height of the denoised image

I_{xy} → Original image pixel value at coordinate (x, y)

I_{xy}^* → Denoised image pixel value at coordinate (x, y)

$E_{\max}^2$ → Largest energy of the image pixels

4.2.2 Second Derivative Measure of Enhancement (SDME)

The formula for SDME value computation [14] is,

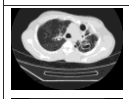
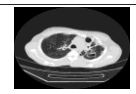
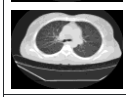
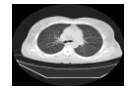
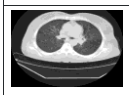
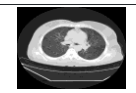
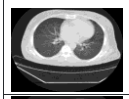
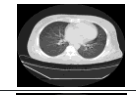
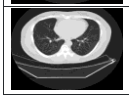
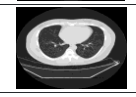
$$SDME = -\frac{1}{k_1 k_2} 20 \ln\left|\frac{I_{\max k,l} - 2I_{center,k,l} + I_{\min k,l}}{I_{\max k,l} + 2I_{center,k,l} + I_{\min k,l}}\right|$$

Where the denoised image is divided into ($k_1 \times k_2$) blocks with odd size, $I_{\max k,l}$ and $I_{\min k,l}$ correspond to the maximum and minimum values of pixels in each block whereas $I_{center,k,l}$ is the value of the intensity of the pixel in the center of each block.

IMPLEMENTATION RESULTS

In this paper, we have compared our proposed denoising technique against existing technique (Sachin D et al. [10]) with five CT images. The performance analysis has been made for the evaluation metrics such as PSNR and SDME. By analyzing the evaluation metrics, the performance of the proposed technique has significantly improved the PSNR and SDME values. Totally, from the Table 1, the proposed denoising technique has achieved better results when compared with the existing technique [10].

Table 1: Comparison Table Of Proposed With Existing Technique [10]

Input CT images	Proposed Denoised CT images	Noise	Variance level	Proposed Technique		Existing[10]	
				PSNR	SDME	PSNR	SDME
		Gaussian	0.02	21.1287	46.7269	16.7166	43.7036
			0.04	19.6213	44.338	14.7828	37.9114
			0.06	18.646	43.9474	13.5612	34.4204
		Salt & Pepper	0.02	21.9445	69.8798	21.634	52.0768
			0.04	21.0776	64.9669	18.567	46.527
			0.06	20.4357	43.101	17.0057	38.0931
		Gaussian	0.02	21.3186	48.9719	16.8026	45.1277
			0.04	19.9728	47.3975	14.8172	38.9988
			0.06	18.6979	46.162	13.6043	35.6109
		Salt & Pepper	0.02	29.841	67.5065	21.8661	52.9996
			0.04	21.7599	65.2206	18.918	49.4154
			0.06	20.5562	44.0129	16.9189	38.2141
		Gaussian	0.02	21.206	48.2659	16.7567	45.1306
			0.04	19.9561	48.3279	14.8153	39.8488
			0.06	18.828	47.5855	13.5965	35.9237
		Salt & Pepper	0.02	22.5698	67.9266	21.7306	63.3859
			0.04	21.2678	64.7767	18.8978	49.0446
			0.06	20.5852	43.7783	17.0635	39.7519
		Gaussian	0.02	21.3496	49.7599	16.7834	45.4059
			0.04	19.9989	46.7261	14.856	39.5777
			0.06	18.9786	46.0037	13.5704	36.3572
		Salt & Pepper	0.02	22.1813	64.3396	21.8897	54.1842
			0.04	21.4148	68.8235	18.7489	48.8421
			0.06	20.8899	43.8492	17.0178	38.2939
		Gaussian	0.02	21.1233	47.992	16.7386	43.3181
			0.04	19.8723	46.4375	14.8244	37.8772
			0.06	18.8407	44.4947	13.5808	34.7142
		Salt & Pepper	0.02	21.7314	65.8095	21.4638	50.4402
			0.04	21.1082	63.1082	18.9884	49.5018
			0.06	19.9906	42.0401	16.9854	38.365

CONCLUSION

In this paper, we propose a new image denoising technique using EMD and Dual Tree Complex Wavelet Packets. We have used two noises, like as Gaussian and salt & pepper for proposed technique. The performance of the proposed image denoising technique is evaluated on the five CT images using the PSNR and SDME. For comparison analysis, our proposed denoising technique is compared with the existing work in various noise levels. The above calculations are being performed on an image of resolution 512×512 and work is being done to remove Gaussian and salt & pepper noise of the images and future plan is to make it valuable for different resolution and for different size of images.

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