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A Hybrid Contourlet Transform for Deblurring and Denoising of Computer Tomography Images

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Abstract: Extraction of clinical information from medical images remains to be a challenging task till date as most of the images obtained from the imaging system are either corrupted by noise and blurring errors due to incorrect focus or motion capture. These image degradation factors influence the information extracted from them which bear a direct consequence on the diagnosis and treatment process. Image deblurring in presence of noise is a basically a tradeoff process as deblurring causes reduction of visual noise but at the same time can hide out essential information in the medical image. A multi resolution transform used in hybrid combination with Richard-Lucy algorithm to deblur the image and at the same time reduce the effect of noise on a CT image is proposed in this study. The filtering process is carried out in the Laplacian domain of the Contourlet transform. The utilization of the multi resolution approximation basically eliminates the need to determine any noise model. Experimental results show a clear improvement in the image quality.

Key words: Deblurring, denoising, multi resolution approximation, richard lucy algorithm, Point Spread Function (PSF)

INTRODUCTION

Medical images are highly significant as they contain critical and vital information regarding a patient. This information is utilized in early detection and treatment of fatal diseases. However, it is very common that these images tend to be corrupted by noises like impulse noise, speckle noise, Gaussian noise etc. Further, the visual quality of the image also is affected by blurring effects occurring due to incorrect focus of the imaging system (Kalotra and Sagar, 2014). Noise usually occur due to the physical imaging process arising due to photonics, quantization, etc and assumed to have a Gaussian distribution with zero mean. Noises resulting during transmission of the medical images are modeled as salt and pepper noise. In general, noises are considered as a degrading factor on the quality of the image and are modeled as a degradation function as:

$$G(x,y) = h(x,y) \times f(x,y) + \eta(x,y) \qquad (1)$$

where:
$h(x, y)$ = Degradation function

$f(x, y)$ = Original image under study
$\eta(x, y)$ = Additive noise

Determining the best estimate to the original image precisely defines image restoration. It is to be noted that image de-blurring problem is basically a trade off approach with image de-noising as de-blurring the image reduces the effect of noise on the image but may cause underlying information to be hidden. The process of blurring is essentially an overlap of nearby pixels in the neighborhood where the pixel gets spread and is characterized by the Point Spread Function (PSF). The blurring could be viewed as a simple convolution process where pixels in a specific area get spread into one pixel. Hence, the de-blurring process is essentially a de-convolution mechanism of obtaining $f(x, y)$ from, the convolution Eq. 1. Hence, the best solution would be to go for a frequency domain approach using the

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convolution theorem or by determination of point spread function. Several wavelet based methods have been utilized as discussed here. The proposed work exploits the directional properties of the contourlet transform developed by Cunha *et al*. (2006). Contourlet transform is characterized by its high directionality and sparse representation. It acts as a good approximator for images with smooth discontinuities or contours which is characteristic of computer tomography or ultrasound images.

Literature review: Image de-noising approach has been carried out in spatial as well as frequency domains. While spatial domain provides de-noising at the pixel level, frequency domain approaches involve algorithms operating on coefficients in the frequency domain. The latter is much preferred especially in medical image processing applications since operation of frequency domain techniques cause little or no visible distortions on the image. Further, the de-noising process may utilize thresholding (Singh and Wadhwani, 2015) methods where a threshold of noise is determined and noise removed using a soft or hard approach (Zhu, 2015). Another strategy would be to utilize fusion rules (Bhadauria and Dewal, 2013). Machine learning methods (Pathak and Sinha, 2014) are also applied for removal of noise where the developed network is trained and fuzzified to minimize the error (Ali and Vathsal, 2010). Rabbani *et al*. (2009) involve usage of discrete complex wavelet transform to convert the image into frequency domain. A gaussian mixture model has been used and minimum mean squared error estimator has been used to reduce noise effectively. On the other hand, de-blurring techniques have also used wavelet techniques like that of Wavelet Vagulette Decomposition (WVD) proposed by Donoho where the coefficients are shrunk and the shrunk coefficients are inverse transformed to obtain the de-blurred image. A recent trend is based on the dual tree complexwavelet transform which does not require the assumption of a noise model for estimation. A vast variety of de-noising approaches using wavelet decomposition could be analyzed from (Ali *et al*., 2010). Since, the focus of this study is a de-blurring approach in presence of noise, the authors would like to highlight significant works carried out in the related area. It is known from literature that there are very few combined algorithms to provide de-blurring as well as de-noising simultaneously. Hence, most of the works involve techniques where medical images are first de-noised and then de-blurred. Blind de-convolution (Cai *et al*., 2012; Levin *et al*., 2011) are well known de-blurring techniques but gives a good performance only when the blur is uniform throughout the image. It operates by finding estimates of the image as well as PSF and undergoes a cyclic process to meet the convergence criterion. The other methods involve the Lucy-Richardson technique (Tai and Lin, 2012) which is iterative in nature and converges to the maximum likelihood solution. The researches of Nishiyama *et al*. (2011) involves creation of a feature space from a training set consisting of blurred images. The test image is compared with the blur kernel and one closest resembling one is used for de-blurring the image under test. The demerit of this method is that the results are not established for images blurred with multiple factors like noise, memory faults, motion shake, etc., however the above discussed methods consider a little or no noise in the image under study. Regularization (Fenge Chen *et al*., 2013) is adopted in some methods to reduce visual noise but its effectiveness reduces with increased noise density. On the other hand, when the blur kernel is known before hand, the combined problem of de-blurring and removal of noise remains a challenge as de-convolution or de-blurring cause amplification of noise. The motivation of the proposed work derives from the concept that a directional filter removes noise while preserving the information under the blur (Zhong *et al*., 2013).

MATERIALS AND METHODS

Proposed work: The process flow of the proposed work is depicted in Fig. 1. The proposed work utilizes the directionality property of the well-known Contourlet transform proposed by Cunha *et al*. (2006). Contourlet transform provides good approximation for images with smooth discontinuities unlike the wavelet transform which gives good approximation for images with sharp discontinuities. Contourlet transform is a multiscale and the directional

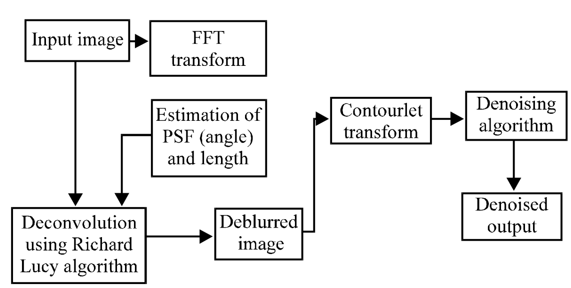

Fig. 1: Flow process of proposed work

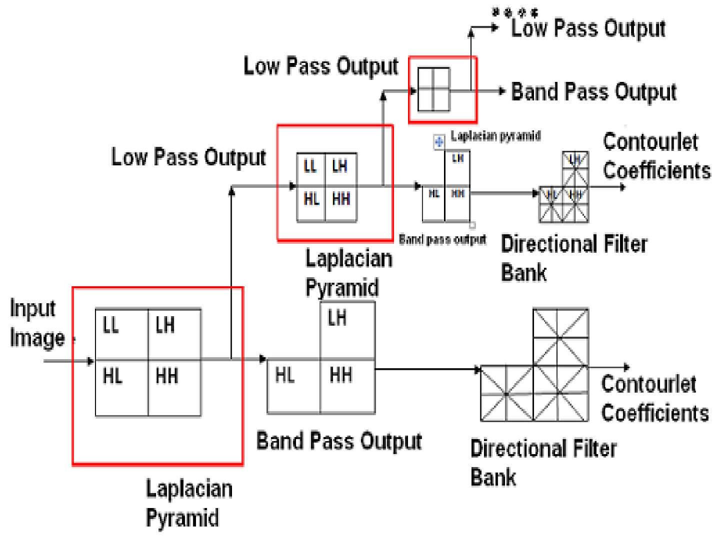

Fig. 2: Contourlet filter bank structure

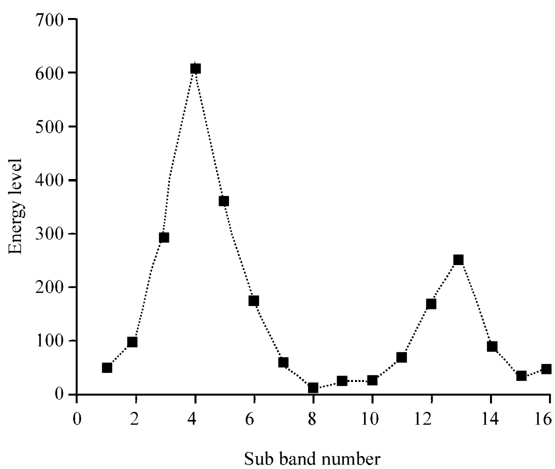

Fig. 3: Energy distribution of contourlet sub bands (CT abdomen image)

decomposition of a signal using a combination of a laplacian pyramid and a directional filter bank. It is expressed as:

$$C_{j,k}(t) = \sum_{i=0}^{n} \sum_{n \in z^2} dk[2n + k_i] \left(\sum_{m \in z^2} fi[m] \right) \varnothing_j - 1, n + m \quad (2)$$

represents the contourlet approximation while d_k and f_i represent the directional and filter equation. 'j' and 'k' represent the scale direction and location. The resultant of the transform is a set of coefficients. Figure 2 illustrates the decomposition of the image into sub bands by a laplacian and directional filter bank structure.

A single level decomposition produces a low pass and band pass version of the input signal. Further decomposition of low pass component result in more coarse details or low frequency components while decomposition of the other sub band extracts more of finer or high frequency components. Since, the objective of the proposed work is deblurring in presence of noise, decomposition of high frequency bands are preferred as noise is characterized by high frequency. The energy of the sub bands are calculated to determine presence of noise. The energy distribution for the abdomen CT input image is show in Fig. 3.

As against the normal denoising methodologies available in the literature the objective of this study is to provide a tradeoff between removal of noise and de-blur. The Contourlet transform can approximate the noise components along the smooth contours while a suitable pre-processing is to be used to remove blur effects. The best known technique could be the inverse filtering. In the frequency domain, an inverse transform of the filtered output would yield the estimate $\bar{x}$ of the original blurred signal x. Though the technique might be simple it has the demerit of introducing extra noise (colored noise) which may cause artifacts in the image under test. A more suitable approach would be to use a de-convolution strategy by determination of the Point Spread Function (PSF). Any pixel p_i could be represented in terms of point spread function as:

$$l_j = \sum PSF_{i,j} p_i \quad (3)$$

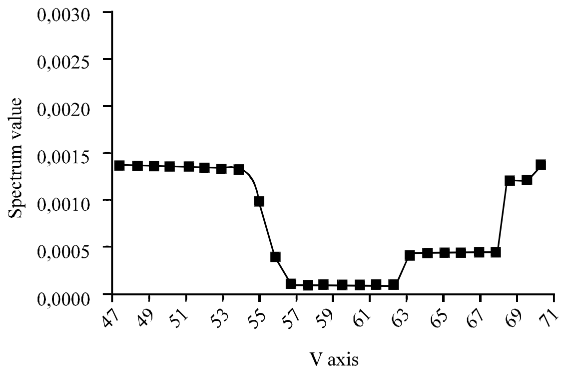

Fig. 4: Gradient distribution (CT abdomen image)

PSF basically involves determination of angle and length. Angle is estimated from the dark region of the Fourier transform while length is obtained from the angle and the parameter ‘d’ which is the distance between the spectrum lines. Deblurring using PSF is essentially a iterative procedure where given the values of PSF and the observed value of the pixel in the image I, the solution would be to determine the best possible pixel which is most similar. The methodology is known as the well-known Richard Lucy algorithm (RL).

The RL algorithms was experimented with both the test images (CT brain and CT abdomen) resulting in a minimum error of 0, maximum error of 1.5 and average error of 0.3 with a standard deviation of 0.4. 220 iterations were done to obtain a PSNR of 47.12dB. The gradient distribution pattern is depicted in Fig. 4. Deblurring normally causes some ringing artifacts which are visible around of the edges of the reconstructed image. But, these artifacts could be greatly minimized by applying basing operators like sobel operator to detect the edges, erosion followed by dilation.

RESULTS AND DISCUSSION

All experiments are conductedwith MATLAB 2011b running on a desktop machine with a Windows7 operating system and an Intel Core i3 processor at 3.07 GHz and 4 GB memory. CT abdomen and brain are employed astest images.To begin with blur kernel and noise (impulsive and multiplicative in nature) are applied on all the experimental images. The quality of the deblurred image is measured by PSNR, defined as:

$$\text{Peak signal to noise ratio} = 10 \log_{10} \frac{255^2}{\text{MSE}} \tag{4}$$

Where MSE is the mean squared error criterion expressed as:

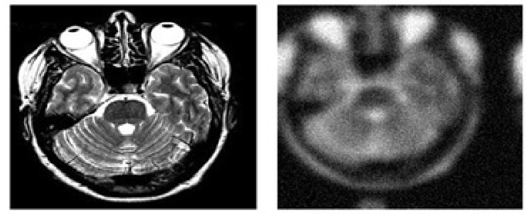

Fig. 5a: Input image (CT abdomen); b) Blurred image

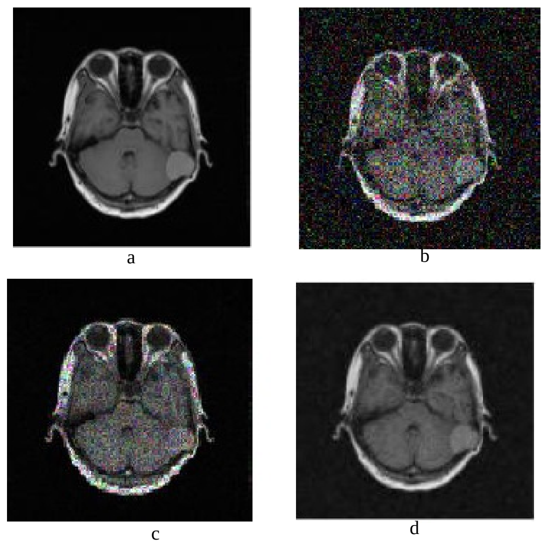

Fig. 6a: Input image (CT brain); b) Noisy image (Gaussian); c) Image corrupted by Speckle; d) Denoised image

$$\text{Mean squared error} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[1(i,j) - 0(i,j)\right]^2 \tag{5}$$

Gaussian noise and Speckle noise models have been used to visualize the effects of additive and multiplicative noises respectively. Figure 5a denotes the input image taken for experimentation while Fig. 5b denotes the blurred image using a blur kernel of radius 3 units. The noise densities were taken to be 0.1, 0.5 and 1.0 magnitudes. The proposed work is compared with the conventional wiener filter used for removal of noise.

Figure 6a and b denote the CT brain image taken as input and Gaussian noise added with a variance of 0.5 and 6c denotes the brain image corrupted by a multiplicative noise. 6d denotes the denoised output using the proposed research.

Table 1 illustrates the performance comparison between various conventional techniques and the proposed work in terms of Signal to Noise Ratio (SNR). It could be seen that the test image blurred and noised to have a SNR of 08.832 and 11.145 have been subjected to wiener filtering,

Table 1: Comparative analysis of SNR versus denoising methods

Type of image /SNR comparison	Signal to noise ratio (dB) SNR of blurred input image	Wiener filter based	Wavelet based (daubechies wavelet)	Proposed hybrid approach
CT brain image	08.832	08.991	09.124	11.284
CT abdomen image	11.145	11.134	11.199	13.012

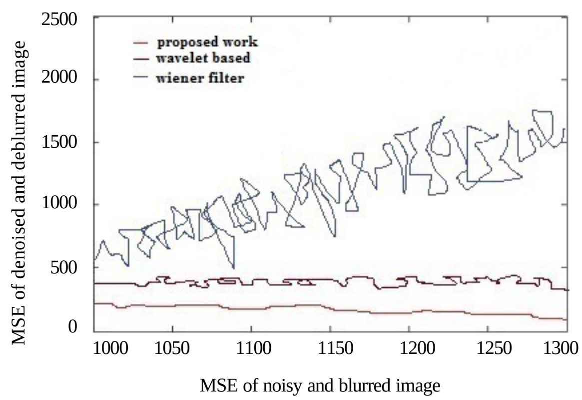

Fig. 7: Performance of error convergence between noisy and denoised image

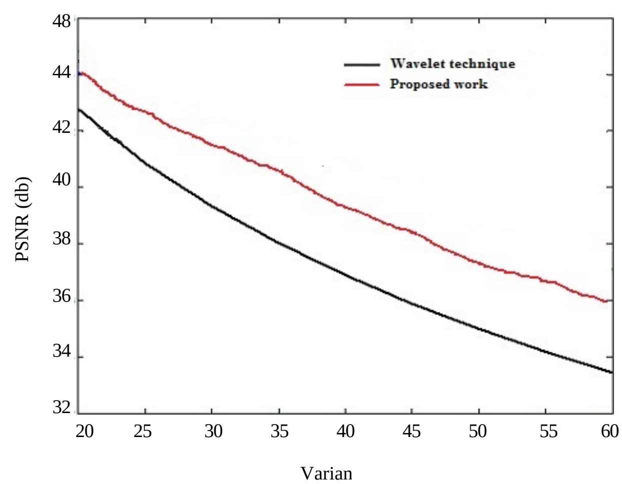

Fig. 8: Performance of denoising technique towards increasing noise variances

wavelet based soft thresholding for denoising and contourlet decomposition and denoising. The proposed work gives a good performance in presence of impulsive as well as multiplicative noise.

Table 1 illustrates the improvement in signal quality in the proposed hybrid approach. The directionality features of the contourlet transform is able to provide better denoising than its predecessors and hence improving the signal quality. Figure 7 depicts the performance of convergence of error between noisy blurred image and denoised and deblurred image in terms of mean squared error. It could be seen that the wiener filtering approach increases the error rate in a more or less linear manner as the variance and blur kernel increases while a smooth convergence could be observed for the proposed work. The result is obtained by testing a CT brain image with a blur kernel of 3 and Gaussian noise with variance of 0.5.

The experiments have also been carried out with gaussian and speckle noise as discussed in previous sections. The performance of the proposed work towards these two noise models has been evaluated in terms of Signal to Noise Ratio (SNR) as depicted in Table 2.

Figure 8 illustrates the performance of the proposed work towards increasing noise densities with variances of 30, 35, 40, 60 etc., the proposed work is found to be relatively stable for high levels of noise variances.

A comparative analysis has been made with existing conventional techniques with the proposed work. It is evident from the observations that the proposed work

Table 2: Comparative analysis of various techniques towards different noise models

	SNR of noisy image (dB)		SNR of denoised image by Wiener filtering (dB)		SNR of denoised image by Wavelet thresholding (dB)		SNR of denoised image by proposed method (dB)	
Image	Gaussian	Speckle	Gaussian	Speckle	Gaussian	Speckle	Gaussian	Speckle
CT Brain	5.01	9.88	6.68	9.93	9.55	13.02	11.01	14.33
CT abdomen	5.12	9.62	6.96	10.01	9.85	13.01	10.85	14.04

provides a relatively high SNR thus improving the signal quality of the deblurred image in presence of noise.

CONCLUSION

A hybrid approach involving contourlet transform and inverse filtering is discussed and implemented in this study. Removal of noise in presence of impulse or multiplicative noise is not that easy as a tradeoff exists between the two factors. Deblurring could result in generation of new noise densities which make the denoising process even more complicated. An inverse filtering is done prior to sub band decomposition to remove the blur effect and directionality properties of contourlet transform has been exploited to identify and approximate noise components along the smooth edges of CT images taken for experimentation. The proposed work has been compared with the conventional wiener filtering method, wavelet method using 4 level decomposition using db6 wavelet function. Results indicate the proposed work marginally outperform the other techniques. Further scope of the work could be to introduce intelligence and learning techniques by using ANFIS structures. Since, deblurring in presence of noise is essentially a tradeoff or optimization problem, genetic based algorithms would be an ideal choice to provide an optimization between the two extremities without affecting the image quality.

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