A Comparative Study on Medical Image Denoising in Hybrid domain

Vishnu M.[*], Arun P. S.[**]

[*] Department of Electronics and Communication, Mar Baselios College of Engineering and Technology

Abstract- The key to medical image denoising technique is to remove the noise while preserving important features. Non-local mean filtering and bilateral filtering are commonly used procedures for medical image denoising. In this paper analysis and comparison of spatial as well as frequency domain methods including bilateral filtering , non-local mean filtering, wavelet thresholding, contourlet thresholding and non-subsampled contourlet transform are done. The non-subsampled contourlet transform applied prior to bilateral and non-local mean filtering gives improved PSNR and perceptual quality. From the results it is also found that introducing transform domain method prior to spatial domain method does not increase the processing time to a much extend.

Index Terms- Bilateral filtering, Contourlet transform, Image denoising, Non-local mean filtering, Non-subsampled contourlet.

I. Introduction

In past years various denoising methods have been introduced for removal of noises from medical images , noises that are mostly occurring in medical images are Gaussian noise, salt and pepper noise[3] and speckle noise [2,4,5]. Many researchers continue to focus attention on it to better the current state of the denoising art and converge to the so called “efficient denoising method”. The two main image denoising methods are spatial domain denoising and transform domain denoising. Spatial domain filters relies on low pass filtering on a group of pixels with the assumption that noise occupies mostly in regions of high frequency spectrum. In the most of spatial filters it has only low pass characteristics hence edges, lines and other fine details will be completely lost due to filtering. While in the case of transform domain denoising the image to be processed must be transformed into the frequency domain using a 2-D image transform.Among the spatial domain methods bilateral filter overcomes the conventional drawbacks of spatial domain methods. It combines gray levels based on both geometric closeness and photometric similarity and prefers near values to distant values in both domain and range and finely preserves the edge information. However it does not give satisfactory results for medical images since real gray levels are polluted seriously and the range filter cannot work properly. This would lead to bring side effect to the denoising results like a polishing look to denoised image, a phenomenon referred as propagation of noise (PoN) and also Implementation of bilateral filter turns out to be rather computationally intensive far real time application. An extension of this bilateral filter which has been proposed by Baudes et al. had put forward Non-Local means image denoising[14,15] which utilizes structural similarity. This denoising method takes full advantage of image redundancy. Though it is an efficient denoising method with the ability to result in proper restoration of the slowly varying signals in homogeneous tissue regions and strongly preserving the tissue boundaries, the accuracy of the similarity weights will be affected by noise and also computation time required is very high. The spatial domain filters if combined can deteriorate the denoising efficiency so we have to move for transform domain methods to cop up with the drawbacks in the above mentioned methods. An effective non-linear denoising technique in transform domain is vishushrink which is proposed by Donoho and Johnstone[27]. Though vishushrink can outperform other denoising techniques it can causes smoothening of images due to the large threshold that is chosen due to its dependence on the number of samples. Therefore it is not a suitable threshold which causes performance variation. The contourlet transform proposed by Do and Vetterli[27] is a geometrical image based transform. It combines the principle of sub-band decomposition and the decomposition of the directional transform. MinhN.Do et al. [33] introduced the non-subsampled contourlet transform (NSCT) which is a fully shift invariant multiscale and multidirectional expansion of the contourlet transform.Since NSCT is not an orthogonal transform the noise variance of sub bands in each directional and each level are different in the NSCT domain. So, the noise variance of every sub band is estimated independently. Thus it provides an effective performance than other denoising schemes.

The main aim of this study is to investigate the performance of denoising methods. The paper is structured as follows: Section II explains the various spatial and transforms domain methods. In section III proposed method is discussed. Simulation results are covered in section IV. Paper concludes in section V.

II. THEORETICAL BACKGROUND

A. *Spatial domain methods*

1) Bilateral Filter

Bilateral filter is very similar to Gaussian convolution. Bilateral filter combines range and domain filtering. It combines gray levels based on both geometric closeness and photometric similarity and prefers near values to distant values in both domain and range. Domain filtering enforces closeness by weighting pixel values with coefficients that fall off with distance. Similarly range filter averages image values with weights that decay with dissimilarity. Bilateral filtering for two gray level images can be described as follows:

$$h(x) = k^{-1}(x)\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(\xi)c(\xi,x)s(f(\xi)).f(x)d\xi \qquad (1)$$

where

$$k(x) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} c(\xi,x)f(f(\xi).f(x))d\xi \qquad (2)$$

$$c(\xi,x) = \exp\left(\frac{-1}{2}\left(\frac{\|\xi - x\|^2}{\sigma_d}\right)^2\right) \qquad (3)$$

measures the geometric closeness between the neighborhood center x and a nearby point ξ and the geometric spread σ_d is chosen based on the desired amount of low pass filtering.

$$s(f(\xi)f(x)) = \exp\left(\frac{-1}{2}\left(\frac{\|f(\xi) - f(x)\|^2}{\sigma_r}\right)^2\right) \qquad (4)$$

meaures the photometric similarity between the pixel at the neighborhood center x and a nearby pixel ξ and the photometric speed $\sigma_s$is set to achieve the desired amount of combination of pixel values.Implementation of bilateral filter turns out to be rather computationally intensive for real time application. Different numerical scheme have been proposed in the past for implementing the filter in real time [11]-[14]. One of recent algorithm is formulated by Choudhary et al. [30].

2) Non-local mean filtering

Non-local mean filter developed is based on a non-local averaging of all pixels in the image. Non-local mean filter takes a mean of all pixels in the image weighted by how similar these pixels are to the target pixel. This results in greater filtering clarity and less loss of detail in the image. Given a noisy image y-{y (i)| i∈I}, the non-local mean filter compute weighted average of all pixels in the image for a pixel i.

$$NL[y](i) = \sum_{j\in I} w(i,j)v(j) \qquad (5)$$

where the family of weights {w(i,j)} depends on the similarity between the pixels i and j and satisfy the usual conditions $0 \le w(i,j) \le 1$ and

$$\sum_j w(i,j) = 1. \qquad (6)$$

Similarity is computed between equally sized patches as they captured the local structures around the sites in consideration. The pixels outside neighboring sites do not contribute to the value of noisy image. To make averaging more robust, the searching window size should be made as large as possible. This would lead to excessively long computation times. Therefore large numbers of fast methods have been developed [32].

B. *Transform Domain methods*

1) Discrete wavelet transform

In a discrete domain, wavelet theory is combined with a filtering theory of signal processing. The coefficients in the wavelet domain have the property that a large number of small coefficients express less important details in an image and a small number of large coefficients keep the information of significance. Therefore denoising in the wavelet domain could be achieved by killing the small coefficients which represent the details as well as the noise. Since noise does not generate exceptions, additive white Gaussian noise after applying wavelet transform is still AWGN.

Wavelet thresholding which is a signal estimation technique that exploits the compatibilities of wavelet transform for signal denoising removes noise by killing coefficients that are insignificant relative to some threshold. The universal thresholding T is an estimate which is asymptotically optimal in the minimax sense and universal threshold is 100% effective only when number of pixels in an image tends to infinity [25], which is an impractical situation.

$$T = \sigma\sqrt{2\log_e L} \qquad (7)$$

where L is the number of random data with zero mean and variance σ/2.

2) Contourlettransform

The contourlet transform combines the principle of subband decomposition and the decomposition and the directional transform. At the first stage, Laplacian pyramid [28] is used to capture the point discontinuities into linear structure. The directional filter bank (DFB) was used to capture the high frequency of the input image; the low frequency content is poorly handled. Therefore low frequencies are removed before applying the DFB. Fig.1shows multi-scale and directional decomposition using a combination of Laplacian pyramid and directional filter bank. Discrete contourlet transform is a composition of perfect reconstruction block.

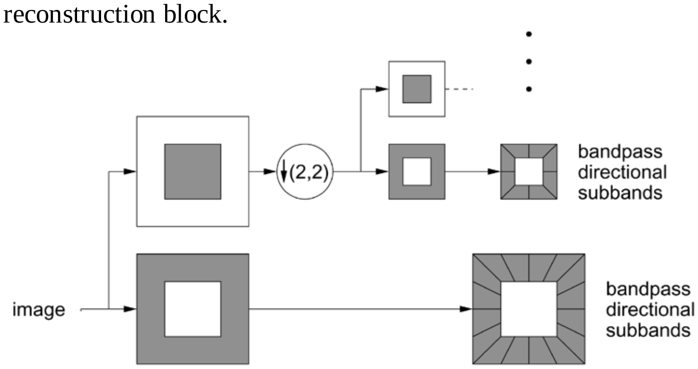

Fig.1.Contourletfilter bank using directional filter and pyramidal filter bank

Simple thresholding scheme applied on the contourlet transform is more effective in removing the noise than it is for the wavelet transform. In contourlet transform the pyramidal filter band has very little redundancy causing aliasing effect.

3) Non-subsampled contourlet transform

Non-subsampled contourlet transform (NSCT) which is a fully shift invariant multiscale and multidirectional expansion of the contourlet transform. In order to avoid frequency aliasing of the contourlet transform and to achieve shift invariance, non-subsampled pyramid filter bank (NSPFB) and non-subsampled directional filter bank (NSDFB) is used. The resulting filter structure approximates the ideal partition of the frequency plane displayed in Fig.2.

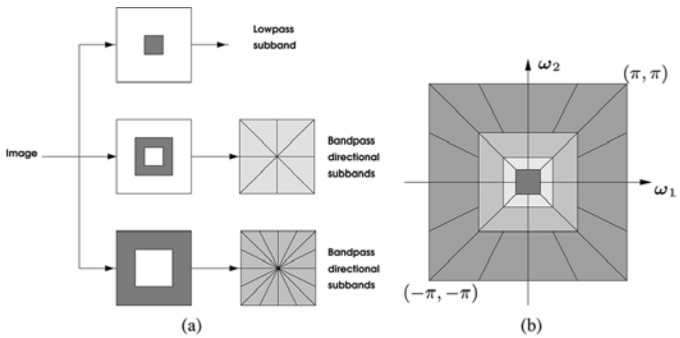

Fig. 2. Non-subsampled contourlet transform a) NSFB structure that implements NSCT. b) Idealized frequency partitioning obtained with the proposed structure

NSCT is not an orthogonal transform the noise variance of sub bands in each directional and each level are different in the NSCT domain. So, the noise variance of every sub band is estimated independently.

III. PROPOSED METHOD

Bilateral filter fails to efficiently remove noise in region of homogeneous physical properties. When noise strikes in homogeneous region the spatial filter used in bilateral filtering most likely perform much lesser than range filters. Therefore noise is retained in the edge information of the image. In the case of non-local mean filter the accuracy of the similarity weigh to will be affected by noise. This also gives the similar phenomenon as bilateral filtering to medical images especially image's tissue region and brain grooves may be weakened by noise. When transform domain methods like wavelet thresholding, contourlet thresholding and NSCT is performed as a preprocessing step denoising becomes much efficient in retaining edges and texture information. Judging from the results NSCT performed as preprocessingstep preserves edge components. So considering NSCT and NLM filtering as a single entity, it is highly suitable for medical image denoising where texture and edge features are for the medical image denoising. The medical denoising entity in hybrid domain is shown in Fig. 3.

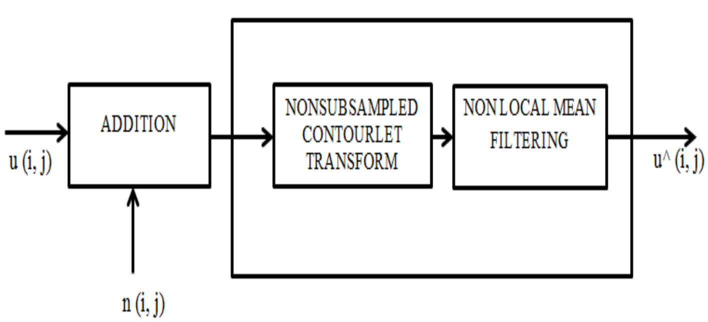

Fig. 3. Medical denoising entity in hybrid domain

where u(i,j) is the original signal n(i,j) denotes the noise introduced into the signal to produce the corrupted image v(i,j) and (i,j) represents the pixel location and u^(i,j) is the denoised image.

IV. SIMULATION RESULTS

CT image of abdomen is shown in Fig.4.is used for simulation. Image has a size of 1024 x 1024 with 256 shades of gray. In denoising method, peak signal to noise ratio (PSNR) is chosen to compare the processed image. But PSNR do not represent human perception of the images. Thus we apply both PSNR measure and the image is also viewed for visual acceptance. The performance of spatial as well as transform domain methods is compared. Then transform domain methods are applied as a preprocessing method in order to improve the performance of bilateral filtering and non-local mean filtering.

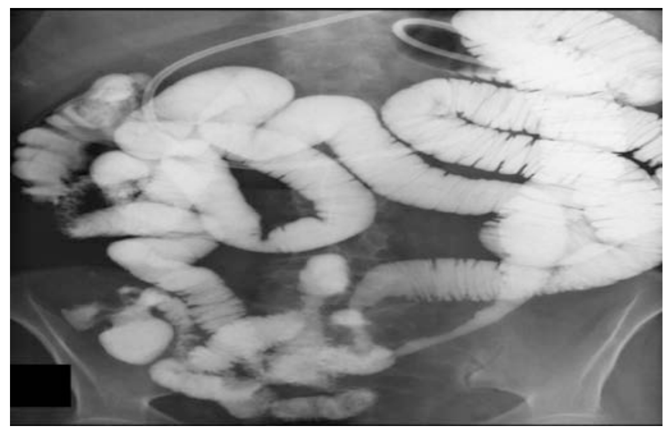

Fig.4. CT image of abdomen

In order to compare the effects of these methods to different additive Gaussian white noise, the original image is corrupted with Gaussian noise with standard deviation varying from 20 to 40. Transform and spatial domain methods are applied to the noise images and PSNR values are recorded.

TABLE I. PSNR COMPARISON OF SPATIAL DOMAIN METHODS

Methods	***Noise***	***Bilateral filtering***	***NLM filtering***
$\sigma = 30$	18.9535	23.5869	24.0978
$\sigma = 40$	16.6847	20.8988	23.5637

TABLE II. PSNR COMPARISON OF TRANSFORM DOMAIN METHODS

Methods	***Noise***	***Wavelet transform***	***Contourlet transform***	***NSCT***
$\sigma = 30$	18.9535	22.9526	24.0978	28.1724
$\sigma = 40$	16.6847	20.0023	23.5637	26.9898

TABLE III. PSNRAND PROCESSING TIME COMPARISON OF IMAGE DENOISING METHODS IN HYBRID DOMAIN

Methods	*PSNR (dB) $\sigma = 30$*	*Processing Time (sec)*	*PSNR (dB) $\sigma = 40$*	*Processing Time (sec)*
Wavelet + Bilateral	23.8569	2.3565	21.6452	2.3655
Contourlet + Bilateral	29.4568	2.4341	26.9524	2.4556
NSCT + Bilateral	31.5698	4.6598	29.6538	4.7698
Wavelet + NLM	23.9525	2.9655	22.9235	3.0127
Contourlet + NLM	29.8684	3.0183	25.2527	3.1235
NSCT + NLM	32.5698	4.7955	31.0864	4.9875

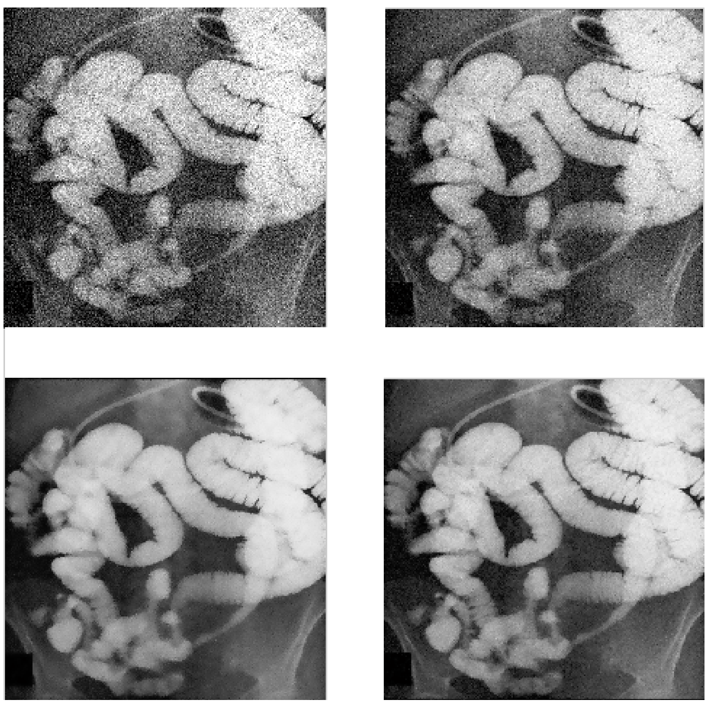

Fig. 5. a) Noisy image ($\sigma = 30$) b) Wavelet and NLM c) Bilateral and contourlet d) NLM and contourlet

From the above tables it is found that among the spatial domain methods non-local mean filter removes more noise than bilateral filter due to its greater filtering clarity. By incorporating NSCT prior to bilateral filtering and non-local mean filtering gives much more visual information. The reason is that bilateral filtering incorporates a spatial filter apart from range filter which gives a smoothing effect. From Table III it is evident that preprocessing with transform domain method does not increase the processing time to much extent.

V. CONCLUSION

In this paper spatial domain, transform domain and hybrid domain methods for medical image denoising are compared. It was found that transform domain method used as a preprocessing step prior to bilateral filtering (hybrid domain) can effectively denoise the image. There is a significant improvement in PSNR and perceptual quality. Also the hybrid domain method requires lesser processing time.

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