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MEDICAL IMAGE DENOISING IN HYBRID DOMAIN USING SWT AND NLM FILTERING

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Abstract-- In medical images noise is inevitably introduced due to various factors. The noise in medical images bring difficulties to medical diagonisis by blurring boundaries and suppressing structural details. Therefore denoising of medical images corrupted by noise is a long established problem in Image processing. 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, stationary wavelet transform are done. The stationary wavelet 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, Image denoising, Non-local mean filtering, Stationary wavelet transform

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 Buades 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. Stationary wavelet transform is a modification of discrete wavelet transform which is used to restore translation invariance property of DWT. Restoration is achieved by suppressing the downsampling step of decimated wavelet transform and inserting zeroes between the filter coefficients instead of upsampling the filter.

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

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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:

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

where

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

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

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.

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

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)| iϵI}, the non-local mean filter compute weighted average of all pixels in the image for a pixel i.

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

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

$$\sum_{j} w(i,j) = 1 \quad (6)$$

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.

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

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

2)Stationary wavelet transform

The Discrete Wavelet Transform is a translation- variant transform. The way to restore the translation invariance is to use some slightly different DWT, called Stationary Wavelet Transform (SWT). It does so by suppressing the down-sampling step of the decimated algorithm and instead up-sampling the filters by inserting zeros between the filter coefficients. Algorithms in which the filter is up-sampled are called “à trous”, meaning “with holes”. In this case, however, although the four images produced (one approximation and three detail images) are at half the resolution of the original, they are the same size as the original image. The approximation images from the undecimated algorithm are therefore represented as levels in a parallelepiped, with the spatial resolution becoming coarser at each higher level and the size remaining the same. This can be visualized in the following Fig.1. The un-decimated algorithm is redundant, meaning some detail information may be retained in adjacent levels of transformation. It also requires more space to store the results of each level of transformation and, although it is shift-invariant, it does not resolve the problem of feature orientation. A previous level of approximation, resolution J−1, can be reconstructed exactly by applying the inverse transform to all four images at resolution J and combining the resulting images. Essentially, the inverse transform involves the same steps as the forward transform, but they are applied in the reverse order.

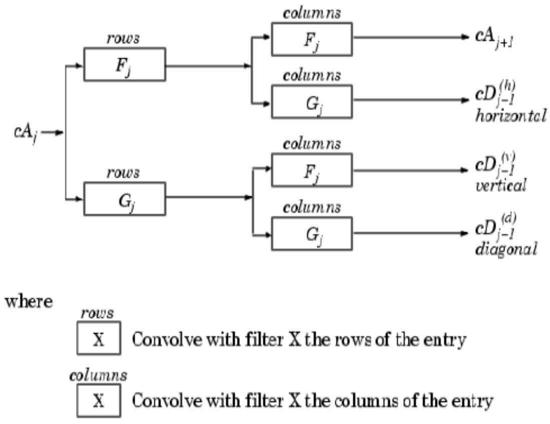

Fig.1. 2D-Stationary Wavelet Transform

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 weight 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 and SWT is performed as a preprocessing step denoising becomes much efficient in retaining edges and texture information. Judging from the results SWT performed as preprocessing step preserves edge components.

Wavelet thresholding which is a signal estimation technique that exploits the capabilities of wavelet transform for signal denoising, remove noise by killing coefficients that are insignificant relative to some threshold. Universal threshold derived by Donoho is hundred percent effective only when number of pixels in an image tends to infinity, which is an impractical situation, therefore a scaling parameter is introduced to the universal threshold. Here we take an arbitrary image of known size and corrupted by a known noise variance. Then scaling factors for the universal threshold is introduced and select the scaling factor corresponding to highest PSNR.

For wavelet thresholding, tabulation with different sets of medical images gives the threshold λ_w to be

$$\lambda_w = 3.854 \times 10^{-11}A^2 - 5.6485 \times 10^{-6}A + 0.6122 \quad (8)$$

For stationary wavelet transform, tabulation with different set of medical images gives the threshold λ_{sw} to be

$$\lambda_{sw} = 3.898 \times 10^{-11}S^2 - 5.5285 \times 10^{-6}S + 0.6122 \quad (9)$$

Where S is a function of noise variance and number of image pixel which is given as

$$S = \sigma \times \sqrt{N} \quad (10)$$

N is the number of pixels of the image under consideration and σ is the standard deviation of noise. So the new threshold is $T_{new} = \lambda_w \times T$ for DWT and $T_{new} = \lambda_{sw} \times T$ for SWT. Proposed stationary wavelet thresholding gives better results compared to proposed wavelet thresholding because of its translational invariant nature.

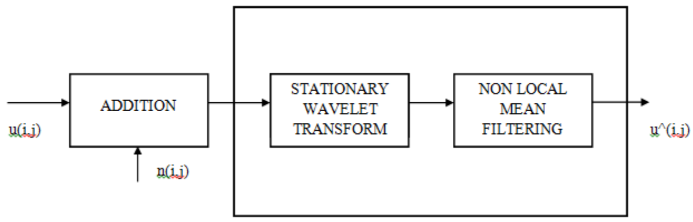

Fig. 2. Medical denoising entity in hybrid domain

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

MRI image of brain is shown in Fig.3.is used for simulation. Image has a size of 512 x 512 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.3. MRI image of brain

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*
σ = 30	18.9535	23.5869	24.0978
σ = 40	16.6847	20.8988	23.5637

TABLE II. PSNR COMPARISON OF TRANSFORM DOMAIN METHODS

Methods	*Noise*	*Wavelet transform*	*Stationary wavelet transform*
σ = 30	18.9535	22.9526	25.0978
σ = 40	16.6847	20.0023	23.5873

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

Methods	*PSNR (dB) σ = 30*	*Processing Time (sec)*	*A. PSNR (dB) σ = 40*	*B. Proces sing Time (sec)*
Wavelet + Bilateral	23.8569	2.3565	21.6452	2.3655
SWT + Bilateral	29.4568	2.4341	26.9524	2.4556
Wavelet + NLM	23.9525	2.9655	22.9235	3.0127
SWT + NLM	29.8684	3.0183	25.2527	3.1235

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 SWT 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.

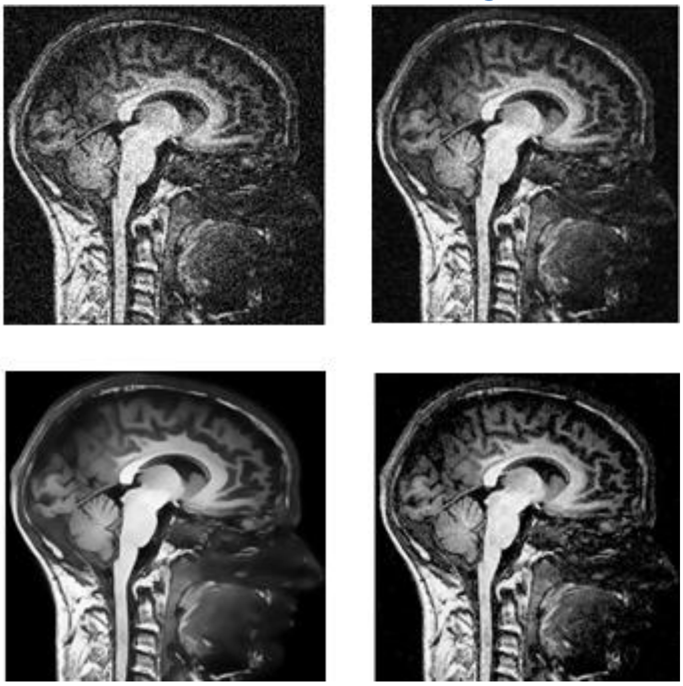

Fig. 4. a) Noisy image (σ = 30) b) Wavelet and NLM
c) Bilateral and SWT d) NLM and SWT

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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