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AN IMPROVED BILATERAL FILTER WITH NOISE ESTIMATION BY WAVELET TRANSFORM FOR CT/MR IMAGES

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Abstract

The medical acquisition systems are susceptible to noise; the noise degrades the quality of the image. The noise reduction is very important in digital image processing. In this proposed work, noise variance estimation on CT images was performed by wavelet transform and the denoising was done by fast bilateral filter. The computation complexity was greatly reduced when compared with the bilateral filter and the performance was superior when compared with the classical spatial domain filters like median, weiner filter. The texture features like contrast, homogeneity, correlation are used to judge the quality of filtering approach. The algorithms are developed in Matlab 2010a and tested on abdomen CT images.

Keywords – denoising , bilateral filter

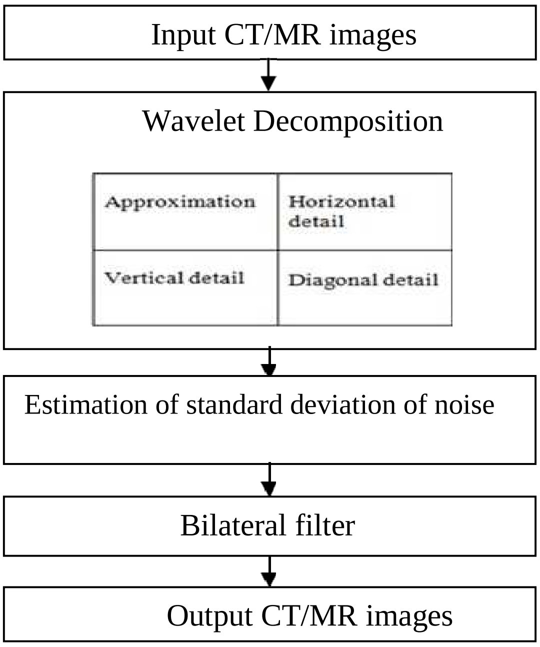
I. INTRODUCTION

The adaptive Fuzzy Switched Noise Reduction filter [2], was used for noise reduction in iris images. The threshold parameters of AFSNR filter was determined from the histogram statistics of the image. Efficient results were produced when compared with Standard median filter and filling method. The algorithm was tested on CASIA V3.0 iris database from the Chinese Academy of Sciences. The authors [3] used decision based median filter for the removal of impulse noise in standard database images. The decision based median filter performance was efficient when compared with standard median filter, improved fast peer group filter and modified decision based un symmetric Trimmed median filter. The decision based median filter has better results for noisy images having densities of 10% to 90%. Spectral subtraction method [8], is an efficient method for the removal of noise in MR images, Spectral subtraction was found to be efficient for suppression of the Additive Gaussian Noise and Random noise. It is well applicable for speech signal processing. The progressive switching median filter [10], was applied for the removal of impulse noise. This filter comprises of two stages, switching and progressive methods. The pixels with impulse noise are detected with switching scheme and filtering of noise is performed in the progressive stage. The decision based median filter [7], was found to be efficient for the denoising of CT images for the automatic detection of liver and liver tumor by feed forward neural network. The robust estimators [6], was used for evaluation of noise variance in an image. The image acquisition protocol was used for acquisition of MR images. The noise could be modeled, even better if a non linear function of image intensity was used. The authors [9], proposed adaptive estimation of the noise power spectrum. The noise was suppressed and the signal component was preserved. Better results were achieved by using the detail sub –band.

The author proposed [1], the merging of both CT and MR images. These images are fused by means of curvelet transform technique. In this paper [4], the background noise was reduced by modified spectral subtraction technique. The algorithm was proposed for minimum distortion in speech signal by considering the perceptual aspects of human ear. The author proposed [10], a combination of both multiresolution bilateral filter with wavelet thresholding. The bilateral filter was applied to the approximation sub-band and wavelet thresholding was applied to detail sub-band. This method helped to reduce the coarse-grain noise in an image on noise estimation from wavelet transform technique was performed . The proposed filtering approach generates efficient restoration results.

II. PROPOSED METHOD

In the proposed work, the noisy CT/MR images was given as input .The input was transformed into four sub band using wavelet transform method, and the standard deviation of the noise was estimated. By using bilateral filter, edge smoothing was performed.



III. NOISE ESTIMATION

Consider an image f_{ij} of size $N \times N$. Assume that the image is corrupted by noise and the corrupted image y_{ij} can be written as follows

$$y_{ij} = f_{ij} + N_{ij} \qquad \text{Eq. 1}$$

From the noisy image signal y_{ij}, we want to find an approximation f_{ij} of the original image f_{ij}. The MR images in general are corrupted by Rician noise and its distribution function is as follows.

$$p(z) = \frac{z}{\sigma^2} exp\left(-\frac{z^2 + I^2}{2\sigma^2}\right) B\left(\frac{zI}{\sigma^2}\right) \qquad \text{Eq. 2}$$

where I is the underlying true intensity, σ is the standard deviation of the noise, and B is the modified zero th order Bessel function of the first kind.

The non-uniform RF coil response in MR imaging produces a bias that varies nonlinearly thereby modulating the intensity of tissues in acquired images. The effect of the bias field is represented by $\alpha(x, y)$ and the corrupted image in equation can be written as

$$f_{bias(x,\ y)} = f_{orginal}(x,\ y)\alpha(x,\ y) + \eta(x,\ y) \qquad \text{Eq. 3}$$

From equation.3,it is clear that the pre-processing algorithm takes into account both Rician noise and bias field effect. The conventional bias field correction techniques are homomorphic filtering, thin-plate or polynomial least squares fitting of selective data points. In the case of CT imaging system, images are corrupted by Gaussian noise.

- When DWT is applied on the noisy image, it is split into four sub-bands (A, H, V, D) by using wavelet filter families (db8)
- The input image is transformed into four bands cA, cH, cV, cD.
- The sub bands are formed by separable applications of horizontal and vertical filters.
- Finest scale coefficients are represented as H, V and D, where D is the detail image.
- Coarse level coefficients are represented as A which is the approximation image.

[cA,cH,cV,cD] = dwt2(X, wname) Eq.4

computes the approximation coefficients matrix cA and details coefficients matrices cH, cV, and cD(horizontal, vertical, and diagonal), obtained by wavelet decomposition of the input matrix X. The _wname‘ string contains the wavelet name.

- The standard deviation of noise is computed as follows

σ^2 □The noise value of noisy images, which is calculated by Roburst Median Estimator.
Estimated from the sub band HH

□□□□□ □ □,□ /0.6745 2 Eq. 5

□ =Standard deviation (STD)
Sigma _d of bilateral filter = Multiplication factor*standard deviation estimated

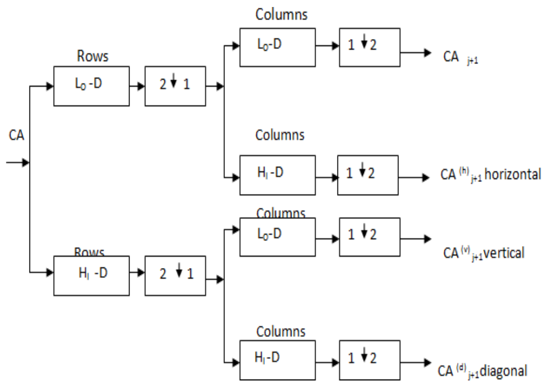


Figure 1.2 Block Diagram of Two-Dimensional DWT

Where $\boxed{2 \downarrow 1}$,Down sample columns: keep the even indexed columns.

$\boxed{1 \downarrow 2}$,Down sample rows: keep the even indexed rows

IV. IMPROVED BILATERAL FILTER

In spatial domain filtering approach, the filtering is carried out by running the mask (template or kernel) on the image from left to right and top to bottom. The centre coefficient of mask is placed in the pixel to be modified and based on four neighbourhood connectivity or eight neighbourhood connectivity, filtering operation is done.

The bilateral filter is a convolution filter and can be used for denoising of CT/MR images in the spatial domain without any loss of edge information .The bilateral filter mask coefficients are identified based on the location of pixels and its gray level values. The bilateral filter coefficients are different for each pixel and depend on the geometric closeness and gray level similarity with the pixel in the centre of the bilateral filter window. The bilateral filter kernel is the product of two sub-kernels, gray-level kernel W_{gk} and distance kernel W_{sk}. The gray level kernel is the function of gray level distance and distance kernel is the function of spatial distance. The gray level kernel can be defined as follows.

$$W_{gk} = exp\left[-\frac{1}{2}\left(\frac{d_{gk}}{\sigma_{gk}}\right)^2\right] \qquad \text{Eq. 6}$$

where d_{gk} is the gray level distance and σ_{gk} is the distribution function for W_{gk}. The distance kernel can be defined as follows.

$$W_{sk} = exp\left[-\frac{1}{2}\left(\frac{d_{sk}}{\sigma_{dk}}\right)^2\right] \qquad \text{Eq.7}$$

where d_{sk} is the spatial distance and σ_{dk} is the distribution function for W_{sk}. The kernel of the bilateral filter is now given by

$$W_{bk} = W_{gk} \times W_{sk} \qquad \text{Eq.8}$$

In bilateral filter, smoothing is done when the pixels in the region are similar and not when the pixels are dissimilar (possibility of edge).

The bilateral filter is thus able to preserve the edges while reducing the noise by performing strong smoothing in the similar pixel region.

V. RESULTS AND DISCUSSION

The simulation is attained with Matlab2013a on a laptop with 32 bit operating system running on Intel(R) Pentium (R) CPU A1018 at 2.10 GHz with 2.00GB RAM. The CT images are acquired from Optima CT machine with 0.6 mm slice thickness. The abdominal CT images of 6 data sets were used and the pathological information is depicted in Table 1.The ethical committee in Mar Ephraem center for Medical Image Processing and Metro Scans and Research Laboratory, Thiruvanathapuram approved the study of CT images of human subjects for research work.

The input images were chosen from six data sets. The satisfactory results were obtained for all the five data sets. The typical images were selected from each data set and the results are depicted below. The input medical image is corrupted by noise and it is subjected to bilateral filtering algorithm. Compared to the classical bilateral filter, superior results were produced, since the parameters are tuned based on the noise estimation from wavelet transform technique. The parameters of the bilateral filter are sigma r and sigma d. The bilateral filter is a spatial domain filter, generated mask is moved throughout the image. It can be viewed as the convolution of two kernels, gray level kernel and distance kernel.

The standard deviation of the gray level kernel is chosen 1.8 and standard deviation of distance kernel is chosen as 5 * standard deviation of noise estimated from the wavelet transform. The kernel size was chosen as 11.

The Daubechies wavelet was chosen for the noise estimation in CT images. The 3 level decomposition is employed and the standard deviation of the noise in the image is estimated as follows.

std_dev2 = (median_hh2/0.6745) Eq.9

The texture characteristics reveal that, adaptive bilateral filter based on noise estimation has good results, since it doesn‘t alter the original texture features, while the noise is filtered.

CONTRAST: It refers to the calculation of the intensity contrast linking pixel and its neighbor over the whole image. At constant image contrast value is 0.In contrast measure, weight increases exponentially (0, 1,4,9) as persists from the diagonal.

Range = [0, size (GLCM,1)-1)^2]

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \qquad \text{Eq.10}$$

CORRELATION: It passes the calculation of the correlation of a pixel and its neighbor over the whole image means it figures out the linear dependency of gray levels on those of neighbouring pixels

$$\sum_{i,j=0}^{N-1} P_{i,j}\frac{(i-\mu_i)(j-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}} \qquad \text{Eq. 11}$$

HOMOGENEITY: In short term it is going by the name of HOM. It passes the value that calculates the tightness of distribution of the elements in the GLCM to the GLCM diagonal. For diagonal GLCM its value is 1 and its range is [0,1]

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)/\,\square \qquad \text{Eq.12}$$

ENERGY**:** Since energy is used for doing work, Thus orderliness. It makes use for the texture that calculates orders in an image. It gives the sum of square elements in GLCM. It is fully different from entropy. When the window is proficient orderly, energy value is high .The square root of ASM(Angular Second Moment) texture character is used as Energy. Its range is [0 1].Since constant image its value is 1.The equation of energy is as follows

$$\sum_{i,j=0} (P_{ij})^2 \qquad \text{Eq. 13}$$

Input image Output image

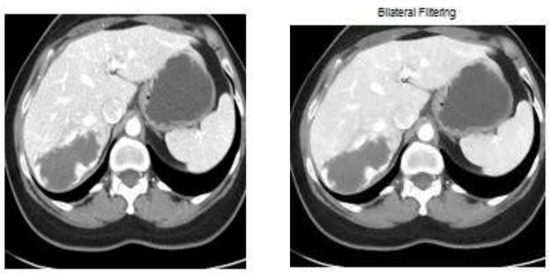


Figure 1.3 Input image and filtered image of P(09).png.

The comparision of the original image with the bilateral filtered image of the abdominal image P(09). png is shown in the above figure.

Table 1.1 Texture characteristics of the input and filtered image of P(09).png

Details	contrast	corre-lation	energy	homo-genity
No filter	0.4960	0.9698	0.6549	0.9911
median filter	0.2842	0.9801	0.1355	0.9208
bi-lateral filter	0.1712	0.9880	0.6615	0.9788

The entropy is given as

$$\square = \sum_{k=0}^{M-1} P_k \log(p_k) \qquad \text{Eq.14}$$

where M is the number of gray levels and p_k is the probability associated with gray level k

Table 1.2 Overall texture characteristics of input and the filtered images for six data sets

Image Details	Entropy of the input image	Entropy of the bilateral filter	Entropy of the median filter
P(09).png	6.5808	1.4164	6.4829
IMG.png	2.8322	0.8974	2.7782
IM0.png	3.2399	1.2013	3.7776
0.01.png	3.6391	1.0690	3.5606
2.png	6.3736	1.3999	6.2854
024.png	6.5068	1.4353	6.4390

VI. CONCLUSION

The entropy of adaptive bilateral filter is low when compared with the median filter and hence the efficiency of adaptive bilateral filter is superior when compared with classical median filter.

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