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RESEARCH PAPER

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RESEARCH ON SPATIAL FILTERS AND HOMOMORPHIC FILTERING METHODS

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Abstract**–**In image processing, denoising is one of the important tasks. Despite the significant research conducted on this topic, the development of efficient denoising methods is still a compelling challenge. In this paper, comparison of Spatial Filters methods with the Homomorphic Filters Methods. The spatial filter methods like Median Filter and Wiener Filter are based on the simple formulas that are proposed by different authors. In Homomorphic Filters Method NormalShrink and BayesShrink are used. The basic idea of homomorphic methods is to denoise the image by applying wavelet transform to the noisy image, then thresholding the detailed wavelet coefficient and inverse transforming the set of thresholded coefficient to obtain the denoised image. In this soft thresholding technique is applied.

INTRODUCTION

Digital images are mostly used in various applications such a2s satellite television, medical field as well as in areas of research and technology. An image contained noise in its acquisition or transmission process. One of the noise is Speckle noise that are mostly found in ultrasound images. Speckle noise significantly degrades the image quality and hence, makes it more difficult for the observer to discriminate fine detail of the images in diagnostic examinations [1]. Speckle is a form of multiplicative noise, which makes visual interpretation difficult [2]. Image denoising is used to remove the noise while retaining as much as possible the important signal features [3]. The purpose of image denoising is to estimate the original image form the noisy data. Image denoising is still remains the challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Various linear techniques have been proposed for signal recovery but for the past few years non-linear techniques are used for better results. Fair amount of research on wavelet transform and threshold selection for image denoising in the recent years.

The wavelet transform was first reported by Donoho & Johnstone [4] and proposed VisuShrink Universal Threshold. The soft thresholding method is analyzed by Donoho [5].Due to its effectiveness and simplicity, it is mostly used for image denoising. The adaptive data-driven threshold called BayesShrink is proposed in [6] and it outperforms VisuShrink. Recently, NormalShrink [7], which is also adaptive threshold is proposed and it is 4% faster than BayesShrink. Over the past decade, there has been considerable interest in using discrete wavelet transform for image denoising [1]-[11]. The discrete wavelet transform is very efficient and has been successfully used in still image processing.

SPATIAL FILTERS

Median Filter:

This filter sorts the surrounding pixels value in the window to an orderly set and replaces the center pixel within the define window with the middle value in the set.

$$\hat{f}(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\} \qquad (1)$$

Median filtering is a non-linear technique that works best with impulse noise (salt & pepper noise) whilst retaining sharp edges in the image.

The main disadvantage is the extra computation time needed to sort the intensity value of each set[12].

Wiener Filter:

Wiener2 lowpass-filters an intensity image that has been degraded by constant power additive noise. Wiener2 uses a pixel wise adaptive Wiener method based on statistics estimated from a local neighborhood of each pixel.

J = wiener2 (I,[m n],noise) filters the image I using pixelwise adaptive Wiener filtering, using neighborhoods of size m-by-n to estimate the local image mean and standard deviation. If you omit the [m n] argument, m and n default to 3. The additive noise (Gaussian white noise) power is assumed to be noise.

[J,noise] = wiener2(I,[m n]) also estimates the additive noise power before doing the filtering. wiener2 returns this estimate in noise.

The wiener2 function applies a Wiener filter (a type of linear filter) to an image adaptively, tailoring itself to the local image variance. Where the variance is large, wiener2 performs little smoothing. Where the variance is small, wiener2 performs more smoothing.

This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image. In addition, there are no design tasks; the wiener2 function handles all preliminary computations and implements the filter for an input image. wiener2, however, does require more computation time than linear filtering.

wiener2 works best when the noise is constant-power ("white") additive noise, such as Gaussian noise.

WAVELET TRANSFORM

Let the signal be { f_{ij}, i, j =1,2….N} where original image is N × N and N is some integer power of 2. The image is corrupted by noise additive white Gaussian noise and is represented as:

$$gij = fij + \sigma\eta ij, i, j = 1, \ldots, N \qquad (2)$$

Where { $\sigma\eta_{ij}$ } are independent and identically distributed (iid) as Normal N(0, σ^2) and independent of { f_{ij} }[1].The goal of denoising is to denoise { g_{ij} } and to estimate the signal f from noisy observations g_{ij} such that minimizes the mean squared error (MSE) [8] .Let W and W^{-1} represent the two-dimensional orthogonal discrete wavelet transform (DWT) and its inverse respectively. Then Y = Wg represents the matrix of wavelet coefficients of g. The 2-D DWT divide the image into four subbands LL, LH, HL, HH [ ] by downsampling by a factor of two in each direction. The subbands LH_k, HL_k, HH_k are called details, where k is the scale varying 1, 2,…..,J and J is the total number of decomposition. The detail coefficients are high-resolution components whereas the subband LL_j is the low-resolution components (coarse level). The size of the subband at scale k is $N/2^k \times N/2^k$. To obtain next coarse level of wavelet coefficients, the decomposition process is iterated on LL subband, splitting it into four smaller subbands in the same way.

HOMOMORPHIC FILTERING METHODS

NormalShrink:

NormalShrink is an adaptive threshold estimation method for image denoising in the wavelet domain based on the generalized Gaussian distribution (GGD) modeling of subband coefficients. It is computationally more efficient and adaptive because the parameters required for estimating the threshold depend on subband data.

The steps of NormalShrink for image denoising are as follows:

a. Take the logarithmic transform of the speckled image.
b. Perform multiscale decomposition of the image corrupted by Gaussian noise using wavelet transform.
c. Estimate the noise variance σ^2 from subband HH1 using formula:

$$\hat{\sigma}^2 = \left[\frac{median(|Y_{ij}|)}{0.6745}\right]^2, \; Y_{ij} \in subband\, HH_1 \qquad (3)$$

d. For each level, compute the scale parameter β using the equation:

$$\beta = \sqrt{\log\left(\frac{L_k}{J}\right)} \qquad (4)$$

e. For each subband (except the lowpass residual) :
a) Compute the standard deviation σ_y.
b) Compute threshold T_N using equation

$$T_N = \frac{\beta\,\hat{\sigma}^2}{\hat{\sigma}_y} \qquad (5)$$

c) Apply soft thresholding to the noisy coefficients.
f. Invert the multiscale decomposition to reconstruct denoised image $\hat{f}$.
g. Take the exponential of the reconstructed image obtained from step 6[7].

BayesShrink:

BayesShrink is an adaptive data-driven threshold for image denoising via wavelet soft-thresholding. Threshold is driven in a Bayesian framework, and we assume Generalized Gaussian Distribution (GGD) for the wavelet coefficients in each detail subband and try to find the threshold T which minimizes the Bayesian Risk.

The steps for image denoising are as follow:

a. Take the logarithmic transform of the speckled image.
b. Perform multiscale decomposition of the log-transformed image using wavelet transform.
c. Estimate the noise variance σ^2 using :

$$\hat{\sigma}^2 = \left[\frac{median(|Y_{ij}|)}{0.6745}\right]^2, \; Y_{ij} \in subband\, HH_1 \qquad (6)$$

d. For each level, compute the scale parameter K using:

$$K = \sqrt{\log(L_k)} \qquad (7)$$

e. For each subband (except the lowpass residual)
a) Compute the standard deviation σ_x

$$\hat{\sigma}_x = \sqrt{max(\hat{\sigma}_y^2 - \hat{\sigma}^2, 0)} \qquad (8)$$

$$\hat{\sigma}_y = \sqrt{\frac{1}{n^2}\sum_{i,j=1}^{n} Y_{ij}^2} \qquad (9)$$

b) Compute threshold T_N , if sub-band variance is greater than noise variance; otherwise set T_N to the maximum coefficient of the subband.

$$T_N = K\frac{\sigma^2}{\sigma_x} \qquad (10)$$

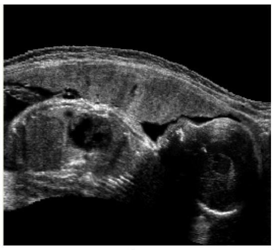
c) Apply soft thresholding to the noisy coefficients.
f. Invert the multiscale decomposition to reconstruct the denoised image $\hat{f}$.
g. Take the exponential of the reconstructed image obtained from step 6 [6].

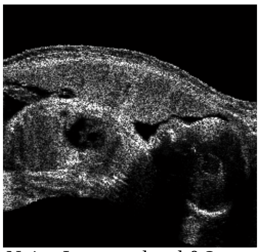
EXPERIMENTAL RESULTS AND DISCUSSIONS

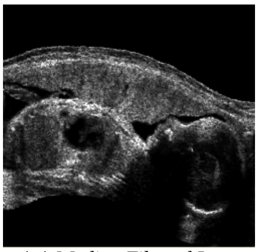
In this section we present the Table 1, Figure 1, containing the results of the spatial filters and homomorphic filters methods. The Figure 1 shows the visual results of Ultrasound image of baby for all methods. The several ultrasound test images of size 512 ×512 are used for performing the experiments at different noise levels σ= 0.1, 0.2, 0.3 and numerical values of results for noise level 0.2 are given in Table 1. We used 3*3 window for the spatial filter methods and 2 level decomposition is used for homomorphic methods. To access the performance of the spatial filters, results are compared with the NormalShrink and BayesShrink. The performance of algorithm is compared on the basis of four quality metrics: peak signal-to-noise ratio (PSNR), signal- to-noise ratio (SNR), coefficient of correlation (CoC), and edge preservation measure (EPI) using the original noise-free image and denoised image. The numerical values of these quality measures at 0.2 noise levels are given in Table 1.and output images are shown in fig 1. The results in fig 1: demonstrate that Normal Shrink gives good performance in terms of visual quality and preserves the detail features to great extend compared to other state-of-the art image denoising techniques. The homomorphic methods better noise removal as well as better preservation of sharp features.

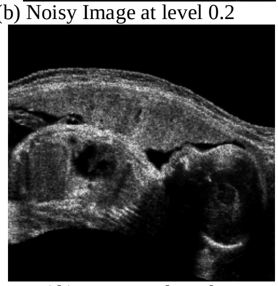
Table 1: Image Quality Measures Obtained By Five Denoised Methods Tested On Ultrasound Image At 0.2 Noise Level

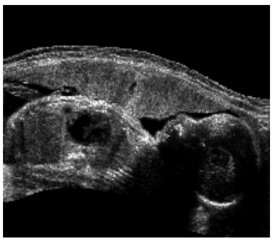
Filters	PSNR	SNR	EPI	CoC
Median Filter	32.2767	5.0444	0.1487	0.9793
Wiener Filter	33.0478	5.8154	0.2277	**0.9924**
NormalShrink	**34.8149**	**7.5826**	**0.5189**	0.9916
BayesShrink	34.6207	7.3885	0.5012	0.9902


(a) Original Image


(b) Noisy Image at level 0.2


(c) Median Filtered Image


(d) Weiner Filtered Image


(e) NormalShrink Denoised Image

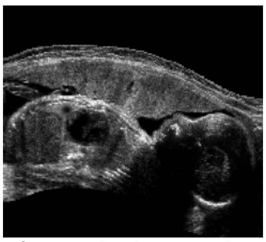

(f) BayesShrink Denoised Image

Figure1: Denoised Image

CONCLUSION

In this paper, different denoising filtering methods are compared. Experiments are conducted to access the better performance from all denoising filtering methods. The result shown in table shows that Homomorphic Filtering Methods produce better result than spatial filters. Wavelet based denoising algorithms uses soft thresholding to provide smoothness and better edge preservation. NormalShrink removes noise significantly and outperforms the BayesShrink.

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