A Novel Threshold Selection Technique for Speckle Filtration from Medical Images

Reeta Soni, Prof. Lalit P Bhaiya

Department of Electronics and Telecommunication
Rungta College of Engineering & Technology, Bhilai (C.G.) India.
Email : reeta25dec@gmail.com

Abstract: this paper presents a wavelet threshold selection technique for speckle noise filtering and comparison of different speckle noise reduction techniques used in medical imaging. Speckle is a multiplicative noise (or signal dependent noise). Because of its property it is more difficult to remove it in comparison to additive noises. Finally all the different techniques are compared for PSNR, SSIM improvement and the processing time required. The simulation results show that that proposed algorithm performs well.

Keywords: image denoising, wavelet transform, speckle noise.

1. Introduction

Noise filtering is an important aspect of the image processing it is required to enhance the quality of the image distorted by many known and unknown noise sources. Since the property of the noise largely depends upon the environment and the sensing schemes a large number of classes defining the behavior of noise are available. In this paper we are specifically dealing with the noise called the speckle noise this is a multiplicative noise hence the noise depends upon the signal strength also.

In the medical imaging the speckle noise is caused by coherent processing of backscattered signals from multiple distributed targets and by data acquisition technique used by the instrument.

The noise greatly affects the image and produces the white and dark spots disturbing the fine details of the image. Since the medical imaging even the smallest details having important role in diagnosis of disease and slight misinterpretation can greatly affect the treatment.

Because of the seriousness of the condition in medical imaging it is a must to design such a processing technique which not only removes the noise without adding artifacts.

The rest of the paper arranged as follow. The second section of the paper presents a brief review of some recent work on the same topic and the third section explains wavelet transform while the fourth unit presents the proposed method followed by the simulation results in the fifth section and at last the conclusion is drawn on the basis of simulation results presented in section six.

2. Previous Work

In this section we present the recent works provides us some useful information for development of the proposed work.

S.Sudha, G.R.Suresh and R.Sukanesh[1] presents a wavelet-based thresholding scheme for noise suppression in ultrasound images. Quantitative and qualitative comparisons of the results obtained by the proposed method with the results achieved from the other speckle noise reduction techniques demonstrate its higher performance for speckle reduction.

T.Ratha Jeyalakshmi and K.Ramar [8]they described and analyzed an algorithm for cleaning speckle noise in ultrasound medical images. Mathematical Morphological operations are used in this algorithm. This algorithm is based on Morphological Image Cleaning algorithm (MIC). The algorithm uses a different technique for reconstructing the features that are lost while removing the noise. For morphological operations it also uses arbitrary structuring elements suitable for the ultrasound images which have speckle noise. Pierrick Coup´e, Pierre Hellier, Charles Kervrann and Christian Barillot [11] proposed a Bayesian Non Local Means-Based Speckle Filtering In their proposal, a new version of the Non Local (NL) Means filter adapted for US images is proposed. Originally developed for Gaussian noise removal, a Bayesian framework is used to adapt the NL means filter for speckle noise. Experiments were carried out on synthetic data sets with different speckle simulations. Nonlocal Means-Based Speckle Filtering for Ultrasound Images is presented by [12] In this method, an adaptation of the nonlocal (NL) means filter is proposed for speckle reduction in ultrasound (US) images. Originally developed for additive white Gaussian noise, we propose to use a Bayesian framework to derive a NL-means filter adapted to a relevant ultrasound noise model. Quantitative results on synthetic data show the performances of the proposed method compared to well-established and state-of-the-art methods. Results on real images demonstrate that the proposed method is able to preserve accurately edges and structural details of the image. M. I. H. Bhuiyan, M. Omair Ahmad, Fellow, IEEE, and M. N. S. Swamy [14] presented Wavelet-Based Despeckling of Medical Ultrasound Images with The Symmetric Normal Inverse Gaussian Prior In their proposal, an efficient wavelet-based method is proposed for despeckling medical ultrasound images. A closed-form Bayesian wavelet based maximum a posteriori denoiser is developed in a homomorphic framework, based on modeling the wavelet coefficients of the log-transform of the reflectivity with a symmetric normal inverse Gaussian (SNIG) prior. A simple method is presented for obtain-ing the parameters of the SNIG prior using local neighbors. Thus, the proposed method is spatially adaptive. Jeny Rajan and M.R. Kaimal [24] In their paper they discuss the speckle reduction in images with the recently proposed Wavelet Embedded Anisotropic Diffusion (WEAD) and Wavelet Embedded Complex Diffusion (WECD). Both these methods are improvements over anisotropic and complex diffusion by adding wavelet based bayes shrink in its second stage. Both WEAD and WECD produce excellent results when compared with the existing speckle reduction filters.

3. Image Filtration techniques and transforms used in this paper

3.1 Wavelet Transform

A wavelet is a wave-like oscillation with amplitude that starts out at zero, increases, and then decreases back to zero. It can typically be visualized as a "brief oscillation" like one might see recorded by a seismograph or heart monitor. Generally, wavelets are purposefully crafted to have specific properties that make them useful for signal processing.

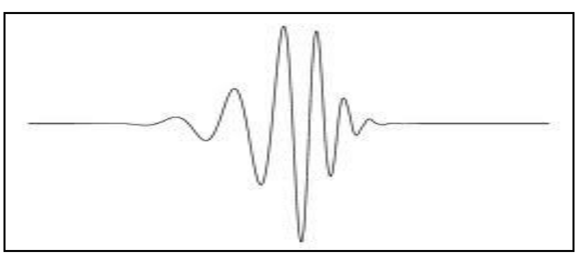

Figure 1: Simple Wavelet.

The wavelet transform replaces the Fourier transform's sinusoidal waves by a family generated by translations and dilations of a window called a wavelet. It takes two arguments: time and scale. A discrete wavelet transform is any wavelet transform for which the wavelets are discretely sampled.

3.2 Wavelet Filtering

After calculating the DWT coefficient form the DWT transform the suppression or elimination of coefficients is performed there are many techniques available for the selection of coefficients and suppression of coefficients and then the inverse DWT is taken to generate the filtered image.

3.3 Median Filter

In signal processing, it is often desirable to be able to perform some kind of noise reduction on an image or signal. The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical pre-processing step to improve the results of later processing (for example, edge detection on an image). Median filtering is very widely used in digital image processing because, under certain conditions, it preserves edges while removing noise (but see discussion below).

The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically. For an even number of entries, there is more than one possible median.

4. Proposed Algorithm

The proposed algorithm works on wavelet thresholding and the threshold is selected by following method

Let the sub band regions of the two-dimensional (2-D) critically sampled wavelet transform. For convenience, let us label the sub bands HH_k, HL_k, and LH_k, where k is the scale, and j is the coarsest scale. The smaller k is, the finer the scale is. Let us also define sub-band P(S). P(S) is the sub-band of the parents of the coefficients of the sub-band S. For example, if S is HH_1, then P(S) is HH_2, or if S is HL_2, then P(S) is HL_3.

To estimate the noise variance σ_n^2 from the noisy wavelet coefficients, a robust median estimator is used from the finest scale wavelet coefficients (HH_1 subband).

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$$\sigma_n^2 = \text{Median}(|\mathbf{y}_i|) / 0.6745$$

Where $\mathbf{y_i}$ is element of sub band HH_1 , $\boldsymbol{\sigma_{y1}}$ and $\boldsymbol{\sigma_{y2}}$ can be found by :

$$\hat{\sigma}_{y1}^2 = \frac{1}{N_1^2}\sum_{y1i\in s} y_{1i}^2$$

$$\hat{\sigma}_{y2}^2 = \frac{1}{N_2^2}\sum_{y2i\in p(s)} y_{2i}^2$$

Where σy_1 and σy_2 are Variances of y_1 and y_2 . Using these variances signal variance σ_1 & σ_2 can be estimated by applying formula given as:

$$\hat{\sigma}_1 = \sqrt{(\hat{\sigma}_{y_1}^2 - \hat{\sigma}_n^2)_+}$$

$$\hat{\sigma}_2 = \sqrt{(\hat{\sigma}_{y_2}^2 - \hat{\sigma}_n^2)_+}$$

Using bivariate shrinkage function

$$\hat{w}_1 = \frac{\left(\sqrt{y_1^2 + y_2^2} - \sqrt{3}\frac{\sigma_n^2}{\sigma}\right)_+ \cdot y_1}{\sqrt{y_1^2 + y_2^2}}$$

Each coefficient is estimated.

The complete process in step by step manner is given below

Step1: Take the original image.

Step2: Distort it with speckle noise of specific variance.

Step3: Take the log of the noisy image.

Step4: Decompose the image in 3 levels DWT.

Step5: filter the coefficients using proposed thresholding algorithm.

Step6: take the inverse of filtered wavelet coefficients to generate filtered image.

5. Experimental Results

The proposed and other algorithms are programmed in MATLAB and the simulated results for PSNR(Peak signal to noise ratio) and SSIM(Structural Similarity) and processing time, with different noise variance.

Table1: Comparison of various techniques (for image distorted by speckle noise of variance 0.5, the PSNR and SSIM of noisy image are 30.45dB and 32.15% respectively).

Method	PSNR(dB)	SSIM(%)	Time(Sec.)
LEE	36.51	72.81	5.17
Median	34.93	61.35	0.147
Adaptive	35.02	79.41	0.127
Wavelet^1	27.96	46.23	1.18
Proposed^1	34.91	76.62	5.66
Wavelet^2	28.38	69.26	0.182
Proposed^2	34.66	79.84	5.36

Superscript 1 denotes soft thresholding and 2 denotes hard thresholding.

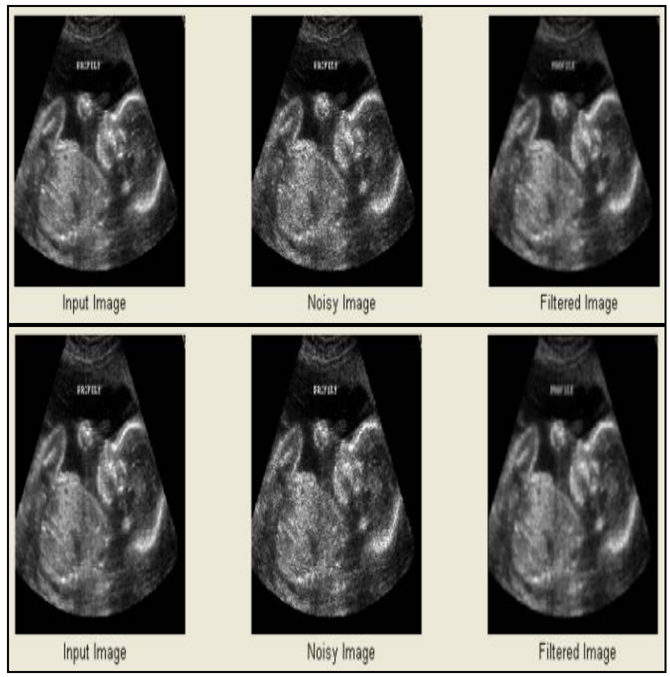

Figure2: images for Proposed^1 method above, Proposed^2 below.

Table2: Comparison of various techniques (for image distorted by speckle noise of variance 0.01, the PSNR and SSIM of noisy image are 37.57dB and 63.44% respectively).

Method	PSNR(dB)	SSIM(%)	Time(Sec.)
LEE	39.35	83.93	5.19
Median	40.55	82.89	0.016
Adaptive	41.23	90.18	0.021
Wavelet^1	33.86	73.35	0.42
Proposed^1	37.29	86.27	5.68
Wavelet^2	33.83	85.19	0.128

Proposed^2	37.50	87.45	5.33

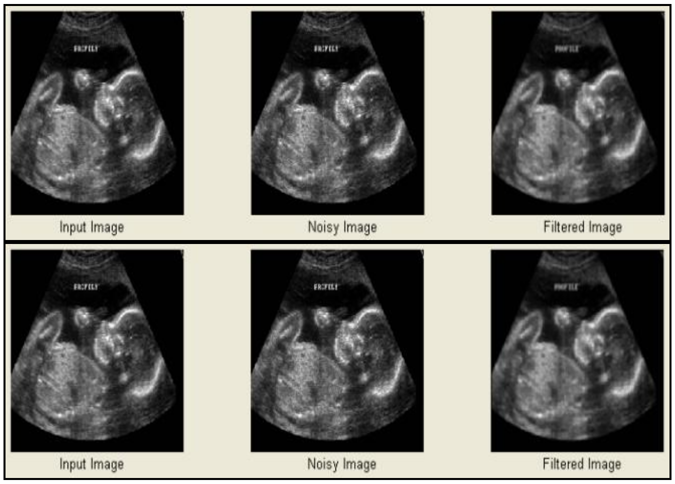

Figure3: images for Proposed^1 method above, Proposed^2 below.

6. Conclusion

The simulation result shows that the wavelet domain techniques take larger time than the spatial techniques and also lags the PSNR and SSIN performance (it adds the artifacts) at the lower noise levels but at higher noise level the wavelet technique outperforms them also the proposed methods provides same PSNR as the normal wavelet technique but it increases the SSIM up to 6% this shows the good enhancement because SSIM reflects the quality on the basis of human eye perception.

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