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Effective Noise Removal Technique for Renal Calculi Images

Dr.P.R.Tamiselvi

Assistant Professor (Senior Grade), School of Computer Technology and Applications
Kongu Engineering College, Perundurai-638 052, Tamilnadu, India

Abstract

The main goal of this work is to development a novel speckle suppression method for kidney ultrasound images in the multiscale wavelet domain. Speckle noise is a arbitrary mottling of the image with bright and dark spots, which destroys fine details, degrades the value of image and discover ability of low-contrast lesions. We have developed Bayesian estimators that use the statistics model along with wavelet transform. We used the proposed model to design both the signal-to-Mean Square Error(S/MSE) and signal to noise ratio (SNR). The resulting noise-removal processors perform non-linear operations on the data.

Keywords: *Ultrasound-Renal Calculi-Speckle Noise- Proposed Approach.*

1. Introduction

Speckle noise affects all coherent imaging systems including Ultrasound (US), laser and SAR imagery. Speckle may appear distinct in different imaging systems. The main purpose of the noise reduction technique is to remove speckle noise without affecting the features of the images. Speckle noise is always manifested in a granular pattern due to image formation under coherent waves. For more than two decades, ultrasonography has been considered as one of the most powerful techniques for imaging human body organs and soft tissue structures. Today, it is being used at an ever-growing rate in the field of medical diagnostic technology. Ultrasonography is often chosen over other medical imaging modalities because it is noninvasive, portable, and versatile, it does not use ionizing radiations, and it is relatively cost effective. The images produced by commercial ultrasound systems are usually optimized for visual interpretation, since they are normally used in real-time diagnostic situations. However, the main disadvantage of ultrasonography is the poor quality of images, which are affected by multiplicative nature of speckle noise.

The wavelet transform or wavelet analysis is probably the most recent solution to overcome the difficulties of the Fourier transform. The use of a fully scalable modulated window solves the signal-cutting problem in wavelet analysis. The window is shifted along the signal and for every position of the window the spectrum is calculated. Then this process is repeated many times with a slightly smaller or longer window for every new cycle. At the end of the process the result will be a collection of time-frequency representations of the signal, all with different resolutions. Because of this group of representations we can speak of a multiresolution analysis. In the wavelets domain normally do not speak about time-frequency representations but about time-scale representations, scale being in a way the opposite of frequency, because the term frequency is reserved for the Fourier transform.

Sudha.S, Suresh.G.R. and Sukanesh.R et al (2009) proposed that Recently there has been significant investigations in medical imaging area using the wavelet transform as a tool for improving medical images from noisy data. Wavelet denoising attempts to remove the noise present in the signal while preserving the signal characteristics, regardless of its frequency content. As the discrete wavelet transform (DWT) corresponds to basis decomposition, it provides a non redundant and unique representation of the signal. Several properties of the wavelet transform, which make this representation attractive for denoising, are

- Multiresolution - image details of different sizes are analyzed at the appropriate resolution scales
- Sparsity - the majority of the wavelet coefficients are small in magnitude
- Edge detection - large wavelet coefficients coincide with image edges and small wavelet coefficients correspond to homogenous areas.
- Edge clustering - the edge coefficients within each sub band tend to form spatially connected clusters

The classical Wiener filter that is not adequate for removing speckle noise, since it is designed mainly for additive noise suppression. To address this issue, Jain A.K

(1989) developed a homomorphic approach which, by taking the logarithm of the image, converts the multiplicative into additive noise, and consequently applies the Wiener filter. Also, the adaptive weighted median filter can effectively suppress speckle but it fails to preserve many useful details, being merely a low pass filter.

Wavelet functions are distinguished from other transformations such as Fourier transform because they not only dissect signals into their component frequencies but also vary the scale at which the component frequencies are analyzed. As a result, wavelets are exceptionally suited for applications such as data compression, noise reduction, and singularity detection in signals (Mariana Carmen Nicolae, Luminita Moraru, and Laura Onose 2010).

The application of wavelets to medical image enhancement has been widely studied. We used the wavelet coefficient transforms and the enhancement algorithms based on the wavelet transforms for noise removal of ultrasound kidney images.

We compared our proposed technique with wiener filters and current state-of-the-art threshold methods applied on actual kidney ultrasound medical images and our proposed method achieved the better performance.

2. Image Noise and Noise Removing Filters

Image noise is the random variation of brightness or color information in images produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector (Charles Boncelet 2005). Image noise is generally regarded as an undesirable by-product of image capture. Although these unwanted fluctuations became known as "noise" by analogy with unwanted sound they are inaudible and such as dithering. The types of Noise are following

• Amplifier noise or Gaussian noise
• Salt-and-pepper noise
• Shot noise or Poisson noise
• Speckle noise

Image Noise and Noise Removing Filters

2.1Amplifier noise or Gaussian noise

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity. In color cameras where more amplification is used in the blue color channel than in the green or red channel, there can be more noise in the blue channel .Amplifier noise is a major part of the "read noise" of an image sensor, that is, of the constant noise level in dark areas of the image(Charles Boncelet 2005).

2.2 Salt-and-pepper noise

An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions (Charles Boncelet 2005). This type of noise can be caused by dead pixels, analog-to-digital converter errors, bit errors in transmission, etc. This can be eliminated in large part by using dark frame subtraction and by interpolating around dark/bright pixels. (Pawan Patidar, Manoj Gupta, Sumit Srivastava, Ashok Kumar Nagawat 2010).

2.3 Shot noise or Poisson noise

Poisson noise or shot noise is a type of electronic noise that occurs when the finite number of particles that carry energy, such as electrons in an electronic circuit or photons in an optical device, is small enough to give rise to detectable statistical fluctuations in a measurement (Charles Boncelet 2005).

2.4 Speckle noise

Speckle noise is a granular noise that inherently exists in and degrades the quality of the ultrasound, active radar and synthetic aperture radar (SAR) images. Speckle noise in conventional radar results from random fluctuations in the return signal from an object that is no bigger than a single image-processing element. It increases the mean grey level of a local area. Speckle noise in ultrasound is generally more serious, causing difficulties for image interpretation. It is caused by coherent processing of backscattered signals from multiple distributed targets. In SAR oceanography (Sedef Kent, Osman Nuri Ocan, and Tolga Ensari 2004), for example, speckle noise is caused by signals from elementary scatters, the gravity-capillary ripples, and manifests as a pedestal image, beneath the image of the sea waves.

3 Speckle Noise in Ultrasound Images

A natural characteristic of ultrasound imaging is the presence of speckle noise. Speckle noise is a random, deterministic, interference pattern in an image. Speckle has negative impact on ultrasound imaging, Radical reduction in contrast resolution may be responsible for the poor effective resolution of ultrasound as compared to other imaging modalities. In case of medical literatures, speckle noise is also known as texture. The texture of the observed speckle pattern does not correspond to underlying structure. The local brightness of the speckle pattern, however, does reflect the local echogenicity of the essential scatterers. The proposed model formulates the ultrasound speckle removal problem starting with a speckle model. Generally, the additive component of the speckle in ultrasound images is less significant than the effect of the multiplicative component.

One of the major drawbacks of ultrasound images is speckle noise presence. Such noise degrades the quality of images, and thus it is crucial to utilize an efficient noise removal scheme to reduce this noise. Imaging speckle is an observable fact that occurs when a coherent source and a non coherent detector are used to interrogate a medium, which is rough on the scale of the wavelength. Speckle occurs especially in images of the liver and kidney whose underlying structures are very small to be resolved by large wavelength ultrasound. The presence of speckle is unwanted since it degrades image quality and it affects the tasks of human interpretation and diagnosis. As a result, speckle filtering is a serious pre processing step for feature extraction, analysis, and recognition from medical imagery measurements. Temporal averaging, median filtering and Wiener filtering are the basis for current speckle reduction methods.

Ultrasound imaging system is widely used diagnostic tool for modern medicine. It is used to do the visualization of muscles, internal organs of the human body, size and structure and injuries. In an ultrasound imaging speckle noise shows its presence while doing the visualization process. A possible generalized model of the speckle imaging as proposed in (Jain A.K 1989) and used in (A. Achim, A. Bezerianos, and P. Tsakalides 2001) is given by

$$g(x,y)=f(x,y)u(x,y)+\xi(x,y)$$

Where g is observed image, f is original image, u multiplicative components, and ξ additive components of the speckle noise called as white Gaussian noise, respectively.

4 Multi-Scale Wavelet based Bayesian Speckle Suppression

The wavelet transform as a powerful tool for recovering signals from noisy data. The main reason for choosing multi-scale bases of decompositions is that the statistics of many natural signals, when decomposed in multi-scale bases, are simplified significantly.

Wavelet analysis is simply the process of decomposing a signal into shifted and scaled versions of a mother (initial) wavelet. The perfect reconstruction is the important property of wavelet analysis, which is the process of reassembling a decomposed signal or image into its original form without loss of information.

The most important properties of wavelets are the regularity and admissibility conditions and these are the properties which gave wavelets their name. It can be represented by using square integral functions $\psi(\omega)$ satisfying the admissibility condition, can be used to first analyze and then reconstruct a signal without loss of information.

$$\int \frac{|\psi(\omega)|^2}{|\omega|} d\omega < +\infty$$

During a two level of decomposition of an image using wavelet, the two-dimensional ultrasound image data is replaced with four blocks. These blocks correspond to the sub bands that represent either low pass filtering or high pass filtering in both directions. The procedure for wavelet decomposition consists of repeated operations on rows and columns of the two-dimensional data. The wavelet transform first performs one step of the transform on all rows. This process produces a matrix in which the left side contains down sampled low pass coefficients of each row, and the right side contains the high pass coefficients. Next, one step of decomposition is applied to all columns; this results in four types of coefficients, this results in four types of coefficients, HH, HL, LH and LL.

The alpha-stable distributions, a family of heavy-tailed densities, are sufficiently flexible and rich to appropriately model wavelet coefficients of images in coding applications. In this work, present a novel speckle suppression method for medical ultrasound images. The proposed processor consists of two major modules: First the wavelet transform is utilized by sub band representation function. Second an effective Bayesian denoising algorithm for the suppression of speckle noise.

Generally, speckle noise is modeled as a multiplicative noise. The speckle reduction is done by multiplying wavelet coefficients by a speckle reduction ratio. It should be mentioned that the speckle reduction aims to improve the subjective image quality and the resulting images should look natural (Nicolae, M.C., Moraru L 2009, Nicolae, M.C., Moraru L., Gogu A2009).

5 Implementation of Multi-Scale Bayesian Filters

The multi-scale decompositions consist of three main steps. In the first step, the raw data are analyzed by means of the wavelet transform, A Bayesian estimator is applied to the wavelet coefficients then the empirical wavelet coefficients are shrunk to estimate the best value for the noise-free signal, and finally, the inverse wavelet transform is used to produce the denoised image is synthesized from the processed wavelet coefficients.

First, the original image is transformed to change multiplicative speckle to additive white noise. Then, the transformed image is analyzed into a multi scale wavelet domain. The proposed system uses the proposed stable model to develop a speckle noise suppression processor that performs a nonlinear function on the data, and relate this nonlinearity to the degree of non-Gaussian of the data.

It is recognized that Bayesian processing is the proper modeling for the prior probability density function (PDF) of the signal. Tsakalides et al. showed that alpha-stable distributions, a family of heavy-tailed densities, are sufficiently flexible and rich to appropriately model wavelet coefficients of images in coding applications. In this paper, we present a novel speckle suppression method for medical ultrasound images. The proposed processor consists of two major modules: A wavelet transform is utilized by sub band representation function and a Bayesian denoising algorithm based on an alpha-stable prior for the signal.

A possible generalized model of the speckle imaging as proposed is given by

$$g(x,y)=a(x,y)b(x,y)+\xi(x,y)$$

Normally the effect of the additive component of the speckle in ultrasound images is less significant than the effect of the multiplicative component. Thus, ignoring the term, one can rewrite

$$g(x,y)=a(x,y)b(x,y)$$

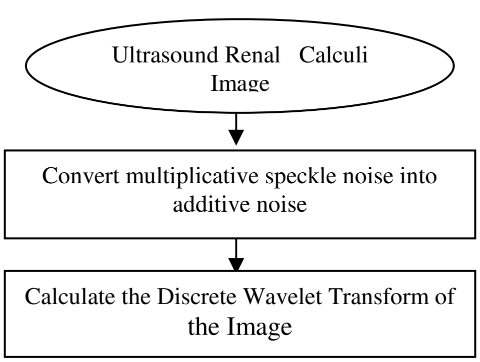
The logarithmic function is applied on both sides to transform the multiplicative noise model into an additive one

$$\text{Log } g(x, y) = \log a(x, y) + \log b(x,y)$$

Can be rewritten as

$$I(x, y) = A(x, y) + B(x,y) + C(x,y)$$

Where I (.), A(.) and B(.) and C(.) are the logarithms of g(.) ,f(.) and , u(.) respectively. In fact, this logarithmic transform constitutes the first preprocessing step of our proposed algorithm as shown in the block diagram depicted in Figure. 1.



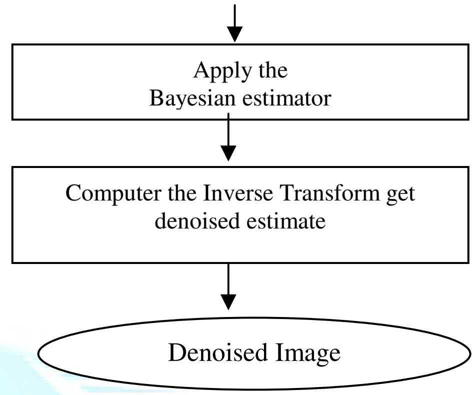


Figure 1 Proposed Denoised Method

The system model designs a Bayesian estimator that recovers the ultrasound kidney image signal component of the wavelet coefficients in ultrasound images by using an alpha-stable prior distribution. The proposed processor is motivated by the modeling based on zero-mean Gaussian model, and it does not depend on the use of ad hoc thresholding and stretching parameters. In a Bayesian model, consider samples of random variables. The Ultrasound image signal factor is designed to an alpha distribution with zero location parameter, while the added noise factor is modeled as a zero-mean Gaussian random variable. Our goal is to find the Bayes risk estimator that reduces the conditional risk, which is the loss averaged over the conditional distribution for the given the set of wavelet coefficients.

The denoised wavelet coefficients are estimated by using a bayesian estimator. The proposed estimator uses a priori knowledge on probability distribution of the signal and noise wavelet coefficients. This estimator performs like a feature detector eliminates speckle noise and preserving the features that are clearly noticeable in the speckled data such as lines and edges.

Bayes' theorem gives the a posteriori probability density function which is based on the measured set of wavelet coefficients. In order to be able to construct the Bayesian processor, estimate the parameters of the signal and noise components of the wavelet coefficients. Then, use the parameters to construct the two prior Probability Density Functions and the nonlinear I/O relationship. The parameterized model for the two PDFs that provides a good fit to the statistics of the ultrasound images is required. The distribution parameters should be estimated from the noisy observations in a well-organized manner.

The Bayesian estimator defined by using the Bayes' theorem, is given by M. Dehghani et al (2003)

$$\hat{s}(d) = \frac{\int P_e(e)P_s(s).s.ds}{\int P_e(e)P_s(s).ds}$$

Where P_e and P_s are the (Probability Density Function) PDFs of the noise and image signal, respectively

The Mean-Square Error (MSE) is minimized by the Bayes risk estimator under a quadratic cost function and is given by the conditional mean. The MSE metric is defined for random variables that take limited second-order moments. In this work, the wavelet coefficient is modeled as an alpha stable random variable that does not have fixed second-order statistics. Hence, the absolute error is used as the loss function.

$$MSE = \frac{\sum (f(i,j) - F(i,j))^2}{S}$$

Where f(i,j) is the original image, F(i,j) is the denoised image, and S is the image size. Wavelet-based Ultrasound Image Denoising is used to calculate the signal-to-MSE (S/MSE) ratio, defined as (Gagnon.L and Jouan.A1997). The signal to Mean Square Error is calculated as

$$S/MSE = 10 \log_{10} \frac{\sum (f(i,j) - F(i,j))^2}{S}$$

Under this loss function, the system is well defined for all random variables with characteristic exponent grater than one. The Bayesian estimator minimizes the Mean Square Error(MSE) and can be exposed to be the conditional median. But conditional density is symmetric around zero; the conditional median coincides with the conditional mean. Hence, the Bayesian estimator for the absolute error cost function is a gain.

In this system noise factor is defined as zero-mean Gaussian model. In other words, the observed signal is a mixture of ultrasound kidney image signal and noise. The system considers the signal and noise components to be independent.

In actual ultrasound images, at the first decomposition levels where the wavelet coefficients arising from noise are predominant, the Bayesian shrinkage function would resemble to that corresponding to low Signal-to-Noise Ratio (SNR). As the resolution decreases, in general the noise level decreases and the nonlinearity applied to the wavelet coefficients corresponds to the high SNR curves gradually approaching the identity function as the SNR becomes very high. The Signal_ to_ Noise Ratio is calculated as

$$SNR = 10\log_{10} \frac{\sigma^2}{\sigma_e^2}$$

Where σ^2 the variance of the original is image and σ_e^2 is the variance of the enhanced image.

The Bayes risk estimator minimizes the Mean-Square Error (MSE). To quantify the achieved performance improvement the standard Signal to Noise Ratio (SNR) is not adequate due to the multiplicative nature of speckle noise. Instead, a common way to achieve this in coherent imaging is to calculate the signal-to-MSE (S/MSE) ratio.

Table 1: Speckle Noise Suppression with multiple Filter in US Kidney Images

Filters/ Error	Proposed Filter	Wiener Filter	Threshold Filter	Non-Filter
Signal to Noise Ratio (SNR)	17.32	14.24	15.63	7.97
Signal to Mean Square Error (S/MSE)	24.02	19.66	17.78	13.2

The results are summarized in Table 1. The measure corresponds to the classical Signal to Noise Ratio and Signal to Mean Square Error of speckle noise. From the table it can be easily seen that our proposed Bayesian approach exhibits the best speckle mitigation performance.

6 Conclusions

The system model proposed, multi-scale nonlinear homomorphic method, effectively suppress the speckle noise in ultrasound kidney images. The system deploys multi-resolution techniques to decompose kidney image into many scales by using the 2-D wavelet transform. With this speckle noise is converted from multiplicative into additive and its characteristics are differentiated from the signal characteristics in each decomposition level.

The comparative evaluation showed that the proposed model is more effective than the wiener and threshold methods, which are ad hoc in the sense that they do not allow for an exact matching of the image and noise distributions at different scales and orientations.

REFERENCES

[1] Sudha.S, Suresh.G.R. and Sukanesh.R(2009)," Speckle Noise Reduction in Ultrasound Images by Wavelet Threshold based on Weighted Variance", International Journal of Computer Theory and Engineering, Vol. 1, No. 1, April 793-8201.

[2] Mariana Carmen Nicolae, Luminiţa Moraru, Laura Onose (2010), "Comparative Approach for Speckle Reduction in Medical Ultrasound Images" Romanian J. Biophys., Vol. 20, No. 1, P. 13–21, Bucharest.

[3] Jain A.K (1989), Digital Image Processing, Englewood Cliffs, N.J: Prentice-Hall, pp. 352–357.

[4] Pawan Patidar, Manoj Gupta, Sumit Srivastava, Ashok Kumar Nagawat(2010)," Image De-noising by Various Filters for Different Noise", International journal of computer Applications(0975-8887) volume 9-No.4, November 45-50.

[5] Charles Boncelet (2005)."Image Noise Models". in Alan C. Bovik. Handbook of Image and Video Processing.

[6] Sedef Kent, Osman Nuri Oçan, and Tolga Ensari (2004). "Speckle Reduction of Synthetic Aperture Radar Images Using Wavelet Filtering". in astrium. EUSAR 2004 Proceedings, 5th European Conference on Synthetic Aperture Radar, May 25–27, 2004, Ulm, Germany.

[7] Nicolae, M.C., Moraru L(2009)., Solution for tissue improving image quality, The Annals of the "Dunarea de Jos" University of Galaţi, Mathematics, Physics, Chemistry, Informatics, fascicle II, Supplement, year II (XXXII), 2009, pp. 27–33.

[8] Nicolae, M.C., Moraru L., Gogu A(2009)., Speckle noise reduction of ultrasound images, Medical Ultrasonography an International Journal of Clinical Imaging, Supplement, 11**,** 2009, 50–51.

[9] D. L. Donoho (1995), "De-noising by soft-thresholding," IEEE Trans. Inform. Theory, vol. 41, pp. 613–627, May 1995.

[10] Xiang .S.H and Zhang Y.T(1996), "Maximization of the signal-to-noise ratio for two dimensional medical ultrasound transducer sensitivity improvement by denoising wavelets," in Proc. Int. Conf. Biomedical Engineering, Hong Kong, June 3–5, 1996.

[11] A. Achim, A. Bezerianos, and P. Tsakalides(2001), "Novel Bayesian multiscale method for speckle removal in medical ultrasound images", IEEE Trans. Med. Imaging, vol. 20, No 8, pp. 772-83, Aug.

[12] Gagnon.L and Jouan.A(1997), Speckle filtering of SAR images - a comparative study between complex-wavelet based and standard filters, SPIE Proc. #3169, 80–91.

[13] M. Dehghani(2003), "Speckle Noise Reduction Using Wavelet Transform", M.Sc. thesis, Nov. 2003.
Pawan Patidar, Manoj Gupta, Sumit Srivastava, Ashok Kumar Nagawat(2010), Image De-noising by Various Filters for Different Noise, Ashok Kumar Nagawat, Volume 9– No.4, November.

[14] Javier Portilla, Vasily Strela, Martin J.Wainwright and Eero P.Simoncelli(2001), " Adaptive Wiener Denoising using a Gaussian Scale Mixture Model in the wavelet Domain", Proceedings of the 8th 5. International Conference of Image Processing Greece. Thessaloniki.

[15] Denver, Fodor I. K, Kamath. C(2003), "Denoising Through Wavelet Shrinkage", An Empirical Study, Journal of Electronic Imaging. 12, pp.151-160.