ANALYSIS OF VARIOUS TECHNIQUES TO REMOVE THE SPECKLE NOISE IN ULTRASOUND IMAGE

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ABSTRACT

In medical image processing, image denoising has become a very essential exercise all through the diagnose. Negotiation between the preservation of useful diagnostic information and noise suppression must be treasured in medical images. In case of ultrasonic images a special type of acoustic noise, technically known as speckle noise, is the major factor of image quality degradation. Many denoising techniques have been proposed for effective suppression of speckle noise. Removing noise from the original image or signal is still a challenging problem for researchers. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided. Insights and potential future trends in the area of denoising are also discussed

Keywords: *ultrasonic images, Speckle noise, Lee filter, kaun filter.*

1. Introduction

Digital images play an important role in daily life application such as television, magnetic resonance imaging, computer tomography as well as in areas of research and technology as well as in areas. Ultrasound images suffer from speckle noise, creating images that appear inferior to those generated by other medical imaging modalities. It is important that medical image be sharp, clear and free of noise. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Speckle noise is observed in ultrasound images whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images.

2. Speckle Noise

Ultrasound imaging is widely used in the field of medicine. It is used for imaging soft tissues in organs like liver, kidney, spleen, uterus, heart; brain etc Ultrasound images are corrupted by speckle noise that affects all coherent imaging systems [1]. Speckle noise is multiplicative noise. Image formation under coherent waves results in a granular pattern known as speckle. The granular pattern is correlated with the surface roughness of an object being imaged.[2]

$$f(x, y)\ g(x, y).\eta m\ (x, y)+ \eta a\ (x, y) \tag{1}$$

Image denoising still remains a challenge for researches because noise removal introduces artifacts and causes blurring of the images. This paper describes different techniques for noise reduction

3. Background

In medical image processing, medical images are corrupted by different type of noises. But ultrasound image mostly corrupted by speckle noise. Ultrasound imaging is widely used in the field of medicine. It is used for imaging soft tissues in organs like liver, kidney, spleen, uterus, heart, brain etc. The common problem in ultrasound image is speckle noise which is caused by the imaging technique used that may be based on coherent waves such as acoustic to laser imaging., de-noising should be performed to improve the image quality for more accurate diagnosis. The main objective of image-de-noising techniques is to remove such noises while retaining as much as possible the important signal features. There are many works on the restoration of images corrupted by noise. Several filters and wavelet techniques are used to remove noise from medical images.

4. Review of Noise Removal Methods

Noise reduction is the process of removing noise from a image. Medical images are corrupted with different kinds of noise while image acquisition. Some noise removal techniques are described below: There are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

Spatial filtering is again divided two ways

5. Non-Linear Filters

With non-linear filters, the noise is removing without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median [8], rank conditioned rank selection [9] and relaxed median [10] have been developed to overcome this drawback.

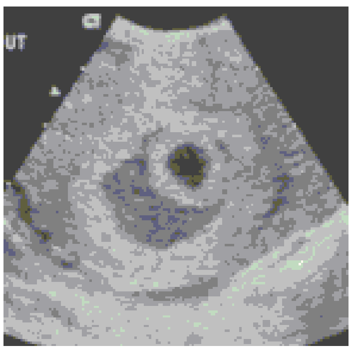

Figure 1: Original Image

6. Linear Filters

A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. The wiener filtering[11] method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size. To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based denoising scheme.

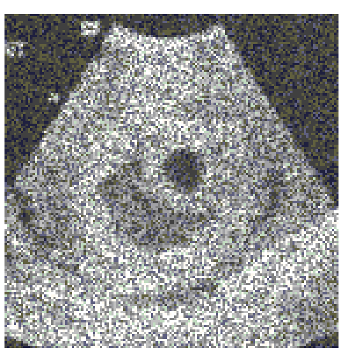

Figure 2: Noisy Image

7. Non-Linear Threshold Filtering

The most investigated domain in denoising using Wavelet Transform is the non-linear coefficient thresholding based methods. The procedure exploits sparsity property of the wavelet transform and the fact that the Wavelet Transform maps white noise in the signal domain to white noise in the transform domain. Thus, while signal energy becomes more concentrated into fewer coefficients in the transform domain, noise energy does not. It is this important principle that enables the separation of signal from noise. The procedure in which small coefficients are removed while others are left untouched is called Hard Thresholding[14]. But the method generates spurious blips, better known as artifacts, in the images as a result of unsuccessful attempts of removing moderately large noise coefficients. To overcome the demerits of hard thresholding, wavelet transform using soft thresholding was also introduced in. In this scheme, coefficients above the threshold are shrunk by the absolute value of the threshold itself. Similar to soft thresholding, other techniques of applying thresholds are semi-soft thresholding and Garrote thresholding. Most of the wavelet shrinkage literature is based on methods for choosing the optimal threshold which can be adaptive or non-adaptive to the image.

8. Non-Adaptive Thresholds

VISUShrink is non-adaptive universal threshold, which depends only on number of data points. It has asymptotic equivalence suggesting best performance in terms of MSE when the number of pixels reaches infinity. VISUShrink is known to yield overly smoothed images because its threshold choice can be unwarrantedly large due to its dependence on the number of pixels in the image.

9. Adaptive Thresholds

SUREShrink uses a hybrid of the universal threshold and the SURE [Stein's Unbiased Risk Estimator] threshold and performs better than VISUShrink. BayesShrink minimizes the Bayes' Risk Estimator function assuming Generalized Gaussian prior and thus yielding data adaptive threshold. BayesShrink outperforms SUREShrink most of the times. Cross Validation replaces wavelet coefficient with the weighted average of neighborhood coefficients to minimize generalized cross validation (GCV) function providing optimum threshold for every coefficient. The assumption that one can distinguish noise from the signal solely based on coefficient magnitudes is violated when noise levels are higher than signal magnitudes. Under this high noise circumstance, the spatial configuration of neighboring wavelet coefficients can play an important role in noise-signal classifications. Signals tend to form meaningful features (e.g. straight lines, curves), while noisy coefficients often scatter randomly.

10. Non-Orthogonal Wavelet Transforms

Undecimated Wavelet Transform (UDWT) has also been used for decomposing the signal to provide visually better solution. Since UDWT is shift invariant it avoids visual artifacts such as pseudo-Gibbs phenomenon. Though the improvement in results is much higher, use of UDWT adds a large overhead of computations thus making it less feasible. In normal hard/soft thresholding was extended to Shift Invariant Discrete Wavelet Transform. In Shift Invariant Wavelet Packet Decomposition (SIWPD) is exploited to obtain number of basis functions. Then using Minimum Description Length principle the Best Basis Function was found out which yielded smallest code length required for description of the given data. Then, thresholding was applied to denoise the data. In addition to UDWT, use of Multiwavelets is explored which further enhances the performance but further increases the computation complexity. The Multiwavelets are obtained by applying more than one mother function (scaling function) to given dataset. Multiwavelets possess properties such as short support, symmetry, and the most importantly higher order of vanishing moments. This combination of shift invariance & Multiwavelets is implemented in which give superior results for the Lena image context of MSE.

11. Wavelet Coefficient Model

This approach focuses on exploiting the properties of Wavelet Transform. This technique identifies close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive The modeling of the wavelet coefficients can either be deterministic or statistical.

12. Deterministic

The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. This approach is adopted in[28] The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree. Thus if a wavelet coefficient has strong presence at particular node then in case of it being signal, its presence should be more pronounced at its parent nodes. If it is noisy coefficient, for instance spurious

13. Speckle Filter

A radiometric enhancement technique that reduces speckle with a minimum loss of information. In speckle filtering a kernel is being moved over each pixel in the image and applying some mathematical calculation by using these pixel values under the kernel and replaced the central pixel with calculated value. By applying these filters smoothing effect is achieved and speckle noise has been reduced.

14. Median Filter

The best known order statistics filter is the median filter in image processing. Median filter are quite popular because, for certain types of random noise. they provide excellent noise reduction capabilities, with considerably less blurring than linear smoothing filters of similar size.it performs much better than arithmetic mean filter in removing salt and pepper noise from image

F^(x,y)= median{g(s,t)}
(s,t) €S xy

14.1 Forest Filter

Achieves a balance between averaging and all pass filter by forming an exponentially shaped filter kernel. Frost filters to reduce speckle while preserving edges in radar images. The Frost filter is an exponentially damped circularly symmetric filter that uses local statistics. The pixel being filtered is replaced with a value calculated based on the distance from the filter center, the damping factor, and the local variance.

Figure 3: Median Filter

Figure 4: Frost Filter

15. Kuan Filter [12]

In this filter given kaun et al., the multiplicative noise model is first transformed into a signal-dependent additive noise model. Then the MMSE criterion was applied to this model. The resulting filter has the same form as the lee filter but with the different weighting function which is given as:

W(t)= 1- C^2/C^2(t)

1+C^2

Kaun filter is much better than the lee filter.

Figure 5: Kuan Filter

16. Wiener Filter [3,11]

The Wiener filter was a filter proposed by Norbert Wiener during the 1940s and published in 1949.Its purpose is to reduce the amount of noise present in a signal by comparison with an estimation of the desired noiseless signal. Weiener filter performs little smoothing. Where the variance is small, wiener performs more smoothing. This approach often produces better results than linear filtering.

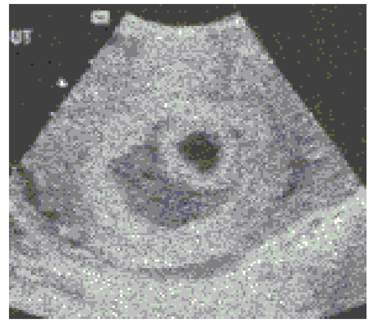

Figure 6: Wiener filter

17. Thresholding Techniques

Thresholding is a simple non- linear technique, which operates on one wavelet coefficient at a time. In its most basic form, each coefficient is threshold by comparing against threshold, if the coefficient is smaller than threshold, set to zero: otherwise it is kept or modified. Replacing the small noisy coefficients by zero and inverse wavelet transform on the result may lead to reconstruction with less noise [13].

Basic procedure for all thresholding method is:

1. Calculate DWT of the image.
2. Threshold the wavelet coefficients.
3. compute IDWT to obtain denoised estimate image

There are two thresholding functions frequently used i.e. soft and hard threshold function proposed by Donoho has been widely used in practice. soft thresholding, Hard-threshlding function keeps the input if it is larger than the threshold: otherwise it is set to zero. Soft threshold function takes the argument and shrinks it toward zero by the threshold. Soft-thresholding rule is chosen over hard thresholding, for the soft thresholding method yields more visually pleasant images over hard thresholding.

17.1 Sure Shrink

A threshold chooser based on stein's unbiased Risk Estimator(SURE) was proposed by Donoho and johnstone and is called as Sure Shrink. It is a combination of the universal threshold and SURE threshold.[14]

17.2 Universal Threshold [15][16]

Donoho in his work proposed Universal threshold (Visu shrink) that over-smooth images. Universal threshold$T = \sigma\sqrt{2\log n}$, with n equal to size of the image $\boldsymbol{\sigma}$ is noise variance. This was determined in an optimal context for soft thresholding with random Gaussian noise. This is easy to implement but noise. decision criteria, resulting in smoother reconstructed data. This estimation does not allow for the content of the data, but only depends on the data size n.

18. Performance Comparison

Table 1: Performance Comparsion of Various Speckles, Wavelet Filters for Ultrasound Image in Terms of PSNR(jpg Format)

σ(PSNR)	0.2	0.4	0.6	0.8
Frost	27.808	24.867	23.158	21.988
Kaun	29.442	27.348	25.910	24.881
Lee	29.405	27.278	26.002	24.980
Bayes	39.027	36.621	34.967	33.992
Median	34.339	32.224	31.323	30.634
Weiner	28.563	25.553	23.890	22.763

18.1 Future Work

Recent researches on multi-scale analysis, especially the curvelet research, provide good opportunity to preserve the edges for image denoising. Therefore, curvelet transform to be utilized for ultrasound image denoising.

CONCLUSION

Negotiation between the preservation of useful diagnostic information and noise suppression must be treasured in medical images. In case of ultrasonic images a special type of acoustic noise, technically known as speckle noise, is the major factor of image quality degradation. Many denoising techniques have been proposed for effective suppression of speckle noise. Removing noise from the original image or signal is still a challenging problem for researchers. After a brief introduction, some popular approaches are classified into different groups and an overview of various algorithms and analysis is provided.

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