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A Review Of Different Image Denoising Methods

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Abstract:

Removing noise from the original signal is still a challenging problem for researchers. In medical image processing, image denoising has become a very essential exercise all through the diagnose. Arbitration between the perpetuation of useful diagnostic information and noise suppression must be treasured in medical images. In general we rely on the intervention of a proficient to control the quality of processed images. In certain cases, for instance in Ultrasound images, the noise can restrain information which is valuable for the general practitioner. Consequently medical images are very inconsistent, and it is crucial to operate case to case.The wavelet transform is a simple and elegant tool that can be used for many digital image processing applications. It overcomes some of the limitations of the Fourier transform with its ability to represent a function simultaneously in the frequency and time domains using a single prototype function (or wavelet) and its scales and shifts. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some significant work in the area of image denoising.

Keywords: *Image Denoising, Digital Image Processing, Ultrasound imaging, Wavelet Transform, Fourier transform*

Introduction

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption.

Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or denoising) giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version.

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 [1] is observed in ultrasound images whereas Rician noise [2] affects MRI images.

Medical images are usually corrupted by noise in its acquisition and Transmission. The main objective of Image denoising techniques is necessary to remove such noises while retaining as much as possible the important signal features. Ultrasonic imaging is a widely used medical imaging procedure because it is economical, comparatively safe, transferable, and adaptable. Though, one of its main shortcomings is the poor quality of images, which are affected by speckle noise. The existence of speckle is unattractive since it disgrace image quality and it affects the tasks of individual interpretation and diagnosis.

The scope of the paper is to focus on noise removal techniques for natural images.

Evolution Of Image Denoising Research

Image Denoising has remained a fundamental problem in the field of image processing. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. The focus was shifted from the Spatial and Fourier domain to the Wavelet transform domain.

Ever since Donoho's Wavelet based thresholding approach was published in 1995, there was a surge in the denoising papers being published. Although Donoho's concept was not revolutionary, his methods did not require tracking or correlation of the wavelet maxima and minima across the different scales as proposed by Mallat [3]. Thus, there was a renewed interest in wavelet based denoising techniques since Donoho [4] demonstrated a simple approach to a difficult problem. Researchers published different ways to compute the parameters for the thresholding of wavelet coefficients.

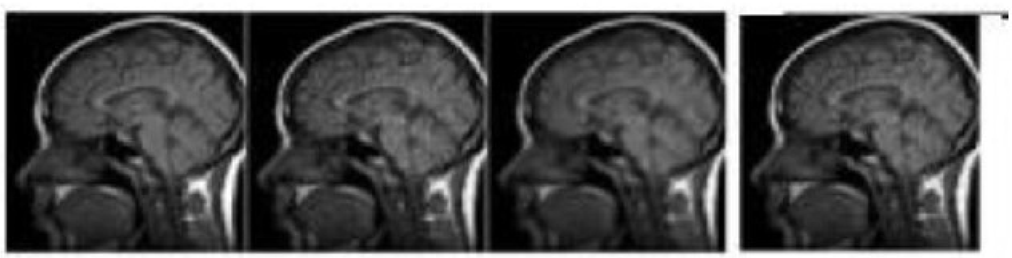
Data adaptive thresholds [5] were introduced to achieve optimum value of threshold. Later efforts found that substantial improvements in perceptual quality could be obtained by translation invariant methods based on thresholding of an Undecimated Wavelet Transform [6]. These thresholding techniques were applied to the nonorthogonal wavelet coefficients to reduce artifacts. Multiwavelets were also used to achieve similar results. Probabilistic models using the statistical properties of the wavelet coefficient seemed to outperform the thresholding techniques and gained ground.

Recently, much effort has been devoted to Bayesian denoising in Wavelet domain. Hidden Markov Models and Gaussian Scale Mixtures have also become popular and more research continues to be published. Tree Structures ordering the wavelet coefficients based on their magnitude, scale and spatial location have been researched. Data adaptive transforms such as Independent Component Analysis (ICA) have been explored for sparse shrinkage. The trend continues to focus on using different statistical models to model the statistical properties of the wavelet coefficients and its neighbors. Future trend will be towards finding more accurate probabilistic models for the distribution of non-orthogonal wavelet coefficients.

Methodology

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Denoising is often a necessary and the first step to be taken before the images data is analyzed. There have been several published algorithms and each approach has its assumptions, advantages, and limitations.[7] In the following section, the review of different methodologies for noise reduction (or denoising) has been presented.

M.I.H. Bhuiyan, M.O. Ahmad, M.N.S. Swamy [8] proposed a new spatially adaptive wavelet-based method in order to reduce the speckle noise from ultrasound images. Spatially adaptive threshold is introduced for denoising the coefficients of log-transformed ultrasound images. The threshold is obtained from a Bayesian maximum a Posteriori estimator. A simple and fast method is provided to estimate the parameters of the prior PDF from the neighbouring coefficients. They showed that the proposed method outperforms several existing techniques in terms of the signal-to-noise ratio, edge preservation index and structural similarity index and visual quality, and in addition, is able to maintain the diagnostically significant details of ultrasound images.

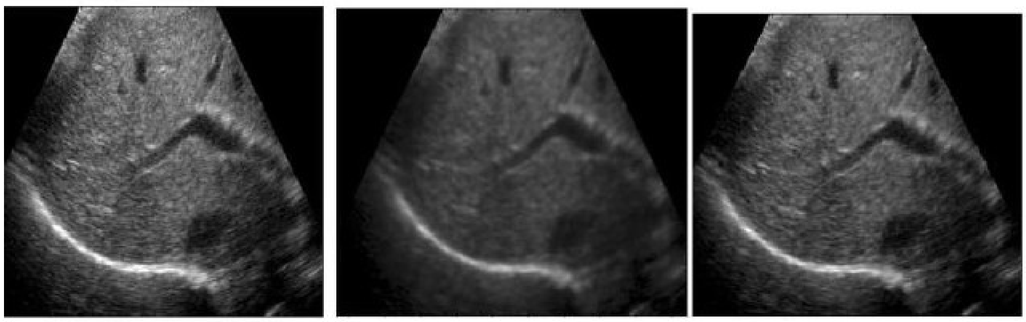


(a) (b) (c) (d)

Figure 1: (a) Noise-free MRI image (b) the corresponding noisy image for a noise standard deviation of 0.7Denoised images obtained using the (c) homomorphic Wiener (d)Bayes-shrink

S. Grace Chang in [9] proposed a spatially adaptive wavelet thresholding method based on context modeling. Here each wavelet coefficient is modeled as a random variable of a generalized Gaussian distribution with an unknown parameter. Context modeling is used to estimate the parameter for each coefficient, which is then used to adapt the thresholding strategy. Experimental results show that spatially adaptive wavelet thresholding yields significantly superior image quality and lower MSE.

Hossein Rabbani, Mansur Vafadust, Purang Abolmaesumi [10] proposed several multiscale nonlinear thresholding methods for ultrasound speckle suppression. The wavelet coefficients of the logarithm of image are modeled as the sum of a noise-free component plus an independent noise. Assuming that the noise-free component has some local mixture distribution (MD), and the noise is either Gaussian or Rayleigh, they derived the minimum mean squared error (MMSE) and the averaged maximum a posteriori (AMAP) estimators for noise reduction. They used Gaussian and Laplacian MD for each noise-free wavelet coefficient to characterize their heavy-tailed property. To evaluate spatially adaptive despeckling methods, they used both real medical ultrasound and synthetically introduced speckle images for speckle suppression. The simulation results showed that this method outperforms several recently and the state-of-the-art techniques qualitatively and quantitatively.



(a) (b) (c)

Figure 2: (a)Input ultrasound image. (b) Homomorphic Wiener [11] (c) Soft threshesholding. [12]

S. Grace Chang [13] proposed an adaptive, data-driven threshold for image denoising via wavelet soft-thresholding. The threshold is derived in a Bayesian framework, and the prior used on the wavelet coefficients is the generalized Gaussian distribution (GGD). The proposed threshold is simple and closed-form, and it is adaptive to each subband because it depends on data-driven estimates of the parameters. Experimental results show that the proposed method, called BayesShrink, is typically within 5% of the MSE. It also outperforms Donoho and Johnstone's SureShrink most of the time.

K. U. Barthel, H. L. Cycon[14] proposed a hybrid wavelet-fractal denoising method. Using a non-subsampled overcomplete wavelet transform the image was presented as a collection of translation invariant copies in different frequency subbands. Within this multiple representation fractal coding was done which tries to approximate a noise free image. The inverse wavelet transform of the fractal collage leads to the denoised image.The results were comparable to some of the most efficient known denoising methods.

(a) (b)

Figure 3: (a)noisy image, PSNR = 20.17 dB (b) fractal denoised image, PSNR = 30.94 dB

Lei Zhang, WeishengDong, DavidZhang, GuangmingShi[15] presented an efficient image denoising scheme by using principal component analysis (PCA) with local pixel grouping (LPG). For a better preservation of image local structures, a pixel and its nearest neighbors are modeled as a vector variable, whose training samples are selected from the local window by using block matching based LPG. The LPG-PCA denoising procedure is iterated one more time to further improve the denoising performance, and the noise level is adaptively adjusted in the second stage. Experimental results on benchmark test images demonstrate that the LPG-PCA method achieves very competitive denoising performance, especially in image fine structure preservation, compared with state-of-the-art denoising algorithms.

M Malfait, Alcatel Antwerp[16] proposed a new method for the suppression of noise in images via the wavelet transform. The method relies on two measures. The first is a classic measure of smoothness of the image and is based on an approximation of the local Holder exponent via the wavelet coefficients. The second, novel measure takes into account geometrical constraints, which are generally valid for natural images. The smoothness measure and the constraints are combined in a Bayesian probabilistic formulation, and are implemented as a Markov random field (MRF) image model. A comparison of quantitative and qualitative results for test images demonstrates the improved noise suppression performance with respect to previous wavelet-based image denoising methods.

Sabita Pal, Rina Mahakud, Madhusmita Sahoo [17] proposed a method for image denoising by the Principal Component Analysis (PCA) with Local Pixel Grouping (LPG). It consists of two stages: image estimation by removing the noise and further refinement of the first stage. The noise is significantly reduced in the first stage; the LPG accuracy will be much improved in the second stage so that the final denoising result is visually much better. Experimental results demonstrates that using LPG-PCA method the denoising performance is improved from first stage to second stage with edge preservation.

R. Sivakumar, D. Nedumaran [18] addressed the Wiener filtering in wavelet domain with soft thresholding. Also, they have compared the efficiency of the wavelet-based thresholding (VisuShrink, BayesShrink and SureShrink) technique in despeckling the medical US images with five other classical speckle reduction filters. The performances of these filters are determined by the statistical quantity measures such as Peak Signal-to-Noise Ratio (PSNR) and Root Mean Square Error (RMSE). Based on the statistical measures and visual quality of the US B-scan images the Wiener filtering with BayesShrink thresholding technique in the waveletdomian performed well over the other filter techniques.

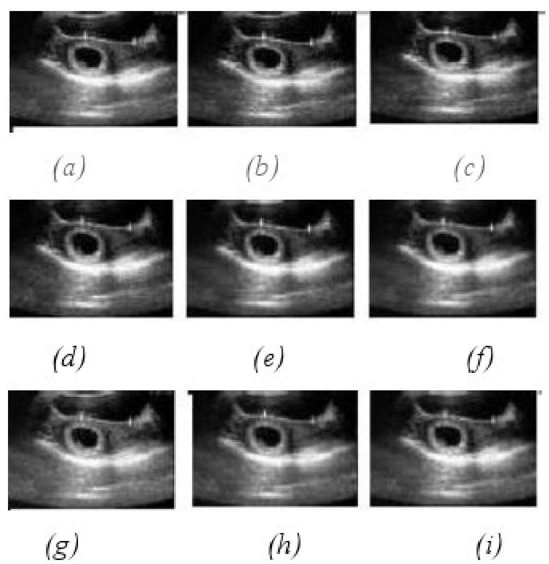


Figure 4: US B-scan image of the bicornuate-pregnancy image (a) Original image, (b) VisuShrink, (c) Kuan filter, (d) Median filter, (e) Frost filter, (f) BayesShrink, (g) Lee filter, (h) Weiner filter and (i) SureShrink

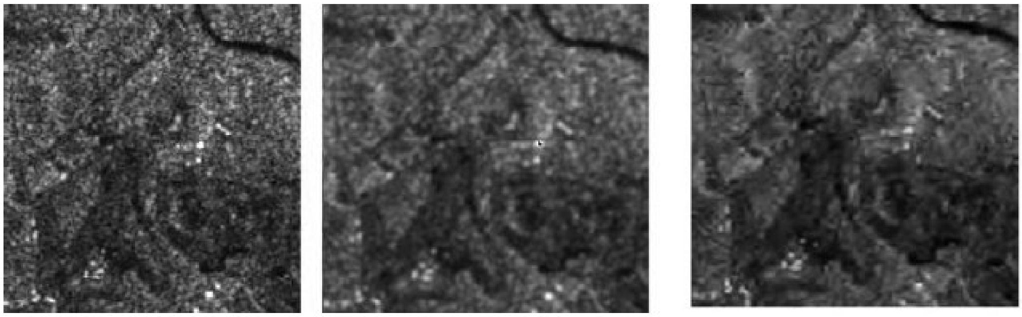
Sheng Yan, Jianping Yuan, Minggang Liu, and Chaohuan Hou [19] proposed a speckle noise reduction method for ultrasound images based on the undecimated wavelet packet transform (UWPT).They applied a nonhomomorphic filtering function combining the generalized likelihood ratio (GenLik) method and local wiener filter technique to suppress speckle noise in UWPT domain. Experimental results of simulated and clinical images show that this method outperforms several powerful speckle reduction methods in terms of speckle reduction as well as in terms of image detail preservation.

S.Sudha, G.R.Suresh, R.Sukanesh[20][21] proposeda new method for suppression of noise in image by fusing the wavelet Denoising technique with optimized thresholding function, improving the denoised results significantly. Simulated noise images are used to evaluate the denoising performance of proposed algorithm along with another wavelet-based denoising algorithm. Experimental result shows that the proposed denoising method outperforms standard wavelet denoising techniques in terms of the PSNR and the preservation of edge information. We have compared this with various denoising methods like wiener filter, Visu Shrink, Oracle Shrink and Bayes Shrink.

(a) (b) (c) (d)

Figure 5: Comparing the performance of (a) Noisy Lena at $\sigma = 30$ with (b) Wiener filter (c) Bayes Shrink and (d) proposed Shrink.

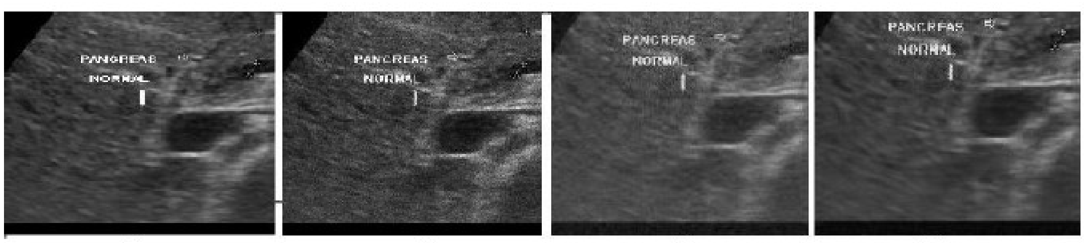
Duan Xinyu and Gao Guowei[22] proposed a new method based on bivariate shrinkage function combined with enhancement of wavelet significant coefficients, which allows us to consider the dependencies between coefficients. In this paper they made the speckle noise model suit the bivariate shrinkage function, and the joint probability density functions (PDF) and noise PDF could be united by MAP to de-noise image, then the wavelet coefficients are enhanced according to a rule whether the coefficient is a significant one or not. The simulation demonstrates that the new algorithm has a better denoised effect comparing with other traditional denoising methods.



(a) (b) (c)

Figure 6: (a) Original image. (b). Lee filter. (c) Proposed method

F. Yousefi Rizi,H.Ahmadi Noubari and S. K. Setarehdan[23][24] made a study of alternative wavelet based ultrasound imaging denoising methods. In particular, contourlet and curvelet techniques withdual tree complex and real and double densitywavelet transform denoising methods were applied to real ultrasound images and results were quantitatively compared. The results show that the curvelet based method performs superior as compared to other methods and can effectively reduce most of the speckle noise content of a given image.



(a) (b) (c) (d)

Figure 7: (a)original image(b)noisy image(c) Contourlet denoising result v=0.03(d) Curvelet denoising result v=0.03

Conclusion

The wavelet transform is a simple and elegant tool that can be used for many digital signal processing applications. It overcomes some of the limitations of the Fourier transform with its ability to represent a function simultaneously in the frequency and time domains using a single prototype function (or wavelet) and its scales and shifts. Use of FFT in filtering has been restricted due to its limitations in providing sparse representation of data. Wavelet Transform is the best suited for performance because of its properties like sparsity, multiresolution and multiscale nature. In addition to performance, issues of computational complexity must also be considered. Thresholding techniques used with the Discrete Wavelet Transform are the simplest to implement. When using Wavelet Transform, Nason emphasized that issue such as choice of primary resolution (the scale level at which to begin thresholding) and choice of analyzing wavelet also have a large influence on the success of the shrinkage procedure. When comparing algorithms, it is very important that researchers do not omit these comparison details. Several papers did not specify the wavelet used neither the level of decomposition of the wavelet transform was mentioned.

It is expected that the future research will focus on building robust statistical models of non-orthogonal wavelet coefficients based on their intra scale and inter scale correlations. Such models can be effectively used for image denoising and compression.

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