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Image Denoising Using Bayes Shrink Method Based On Wavelet Transform

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Abstract

In this paper, a denoising method is presented for noise reduction in Ultrasound (US) images. This paper proposes an efficient method based on linear filtering for images which is corrupted due to Gaussian noise. The method consists in linear filtering of proper wavelet coefficients of the image, corresponding to diagonal and vertical details. The proposed denoising method has good performance and the effectiveness of the proposed method is well demonstrated by experiments on both standard Boat image and real US images.

Keywords: Denoising, Gaussian noise, Wavelet transforms, 2-D linear filtering.

I. Introduction

Digital image processing is a technique in which computer algorithms can be applied to process a digital image. Medical imaging comprises of different imaging modalities and used to represent the internal part of human body for diagnostic and treatment purposes. Therefore, medical images play an important role in the improvement of public health in all groups. In this paper different standard Boat image and US image which are corrupted due to Gaussian noise are used for the purpose of denoising. Gaussian noise is a statistical noise that has a probability density function equal to the normal distribution, which is called as Gaussian distribution. Several approaches [1-4] have been proposed to suppress the noise from digital images and many of them are based on adaptive wavelet thresholding schemes that depend on edge strength or context modeling to improve the efficiency of the denoising procedure [3]. Some of these techniques are based on wavelet representation which is computed with a pyramidal algorithm based on convolutions with quadrature mirror filters [5], a pure linear expansion of thresholds methodology is used to design and optimize a wide class of transform-domain thresholding algorithms [6]. Coefficients statistical model is used for removing noise from digital image that applied over a complete multiscale orientation [7]. An alternative complementary framework is used for quality assessment which is based on the degradation of structural information [8]. An orthonormal wavelet image denoising method is used which directly parametrize the denoising process and then minimize the estimation of mean square error between the original image and denoised image [9]. Multiresolution structure and sparsity of wavelets are employed by nonlocal dictionary learning in each decomposition level of the wavelets. A method based on multiresolution structure and sparsity of wavelets by nonlocal dictionary learning in each decomposition level of wavelet transform for image denoising [10]. Artifacts in medical ultrasound image can be removed by a method based on soft thresholding of the wavelet coefficients. Artifacts are commonly encountered in medical ultrasound imaging due to multi-path reflection, reverberation, and enhancement [11]. Several 2D and 3D image denoising filters are implemented on digital signal processing, evaluating real-time mode in the image processing [12]. Multiscale speckle reduction method is used to transform the logarithmic image into the oriented dual-tree complex wavelet domain to enhance the medical ultrasound images and improve clinical diagnosis [13]. An adaptive weighted median filter based on the weighted median is used to reduce speckle noise. It originates from the median filter through the introduction of weight coefficients [14]. Wavelet thresholding is a signal estimation technique that exploits the capabilities of wavelet transform for denoising purpose. It removes noises that are insignificant relative to some threshold, and turns out to be effective and simple, depend on the choice of a thresholding parameter and provide a great extent to the efficacy of denoising by threshold determination. BayesShrink is an adaptive data-driven threshold for image denoising [1]. It gives best threshold as compared to other for denoising images.

Thus the focus of this paper is image denoising. The main aim of an image denoising algorithm is to achieve noise reduction from images. In this context, wavelet-based methods are of particular interest. In the wavelet domain, the noise is uniformly spread throughout coefficients while most of the image information is concentrated in a few large coefficients. The paper is organized as follows. In section II, Image denoising method is described. Section III shows the performance of proposed method for image denoising and calculates parameters like Peak signal to noise ratio and SSIM. Finally, the paper is concluded in Section IV.

II. Proposed Method

Image denoising has been a well studied problem in the field of image processing. In this paper a wavelet based linear filtering method is proposed for the purpose of denoising.

A. 2-D Discrete Wavelet Transform

Wavelet transform decomposes an image in sub sampled images in which the low-pass filter approximation consists of the sub sampled images and the details of the images corresponds to high pass filter in each direction [1, 3, 4]. In particular, first-level 2-D discrete wavelet decomposition produces four sub-images A1, H1, V1 and D1, where A1 is derived by low pass filtering and twofold decimation along the row and column direction [11], whereas H1, V1 and D1 represent the horizontal, vertical and diagonal details respectively. Denoising is obtained by inverse wavelet transform after elimination of a single sub-image chosen among H1, V1 and D1 [1].

During transmission the image I is corrupted by Gaussian noise with independent and identically distributed mean and standard deviation. First logical step is to compute the denoised image. Suppose that a given image I= $\{I_{xy}$, x = 1, …, M, y = 1, …, N$\}$ has been corrupted by Gaussian noise according to the following model

$$s = I + n \quad (1)$$

Where n represents the noise and s is observed as noisy image. Here, the noise is identically distributed and statistically independent.

The decomposition of an image (s) into coefficients through a discrete wavelet transform W can be expressed as

$$G = W(s) \quad (2)$$

The application of the discrete wavelet transform decomposes the input image into different frequency sub bands, labeled as LL_m, LH_n, HL_n and HH_n, n =1, 2, …, J, where the subscript indicates the n-th resolution level of wavelet transform and J is the largest scale in the decomposition. These sub bands contain different information about the image. The lowest frequency LL_m sub band which is obtained by low-pass filtering along with x and y directions and corresponds to a coarse approximation of the image signal. The LH_n, HL_n and HH_n sub bands correspond to all details of the image signal. The second step is to leave unchanged the horizontal coefficients and to smooth an image instead of eliminating the diagonal and vertical details. The smoothing of the diagonal and vertical coefficients has been done by means of Gaussian 2-D filters.

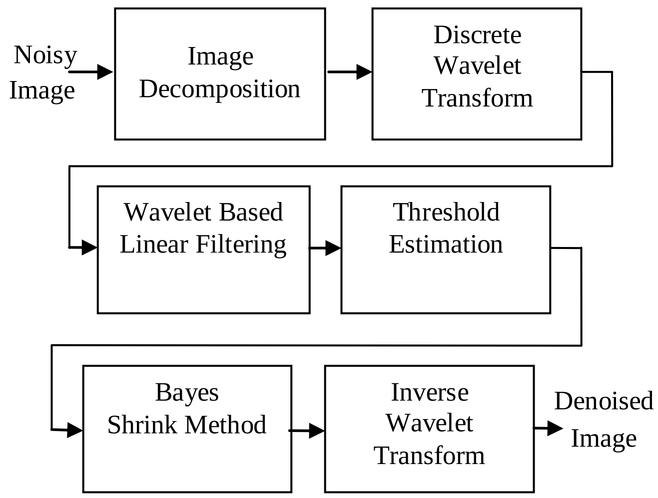

Figure 1 Block Diagram of Proposed Method

Figure 1 shows the block diagram of the proposed method. Wavelet based image decomposition is performed on the noisy image to transform noisy image data into wavelet domain. Then 2D discrete wavelet transform is applied to produce four sub images. Wavelet based linear filtering is applied to sub images obtained via decomposition. Thresholding is done by BayesShrink method to yield superior image quality. By using this method, shrinking the wavelet transform is performed to remove the low amplitude noise or undesired signal in wavelet domain. Now, find the threshold that minimizes the Bayesian risk. Finally, compute the Inverse Discrete Wavelet Transform (IDWT) to get the denoised image.

B. Wavelet Thresholding

The goal of this paper is to estimate the signal from noisy observations such that the mean squared error is minimised. Let W and W^{-1} denote the two-dimensional orthogonal discrete wavelet transform (DWT) matrix and its inverse respectively. Then G = W(s) represents the matrix of wavelet coefficients of (s) having four sub-bands (LL, LH, HL and HH). The sub-bands HH_n, HL_n, LL_n are called details of an image where n is the scale varying from 1, 2, . . ., k, and k is the total number of decompositions levels.

Here threshold estimation criteria called BayesShirnk estimation, as described below. BayesShrink [4,7] assumes generalized Gaussian distribution for the wavelet coefficients in each detail of sub band and uses a Bayesian mathematical framework to find the best threshold that minimizes the Bayesian risk , expressed as

$$\sigma_B = \frac{\lambda^2_{\text{noise}}}{\lambda_{\text{Signal}}} = \frac{\lambda^2_{\text{noise}}}{\sqrt{\max(\lambda^2_G - \lambda^2_{\text{noise}}, 0)}} \qquad (3)$$

Where $\lambda^2_G = \frac{1}{P_s}\sum_{x,y=1}^{Ns} V_{xy}^2$ and P_s is the number of wavelet coefficients V_{xy} on the sub band under consideration. A robust estimate of noise variance uses the median absolute value of the wavelet coefficients, which is insensitive to isolated outliers of potentially high amplitude [2], defined as

$$\lambda_{\text{noise}} = \frac{\text{median}(|V_{xy}|)}{0.6745}, \quad V_{xy} \in \text{ subband HH} \qquad (4)$$

Where V_{xy} is HH wavelet coefficients which forms the finest decomposition levels.

III. Simulation Results

Results were represented for standard Boat image as well as medical US image. A standard gray scale Boat image of 256x256 dimensions is used for the denoising purpose. All the images are corrupted artificially due to Gaussian noise of different noise variances. Wavelet transform is used to decompose the image into sub images. Then wavelet based de-noised algorithm is applied. Peak signal to noise ratio (PSNR) and structural similarity index (SSIM) are the parameters for objective evaluation of denoised image. Table 1 shows the comparison of PSNR values obtained using the wavelet based denoising method given in [1] and for the proposed method. The value of PSNR is obtained for gray scale standard Boat image of 256x256 dimensions.

Table 1 PSNR for Boat Image

Image	Noise Level (σ)	PSNR(dB)	
		Wavelet Based Denoising Method[1]	Proposed Method
Boat Image (256x256)	10	32.52	34.69
	15	30.81	32.35
	20	29.43	30.66
	25	28.48	29.30
	30	27.66	28.29
	35	27.05	27.46

Figure 2 compares the PSNR between proposed method and the wavelet based denoising method. From the PSNR curve, it can be seen that as noise level increases then PSNR decreases at different noise levels of Gaussian noise. From the comparison curve it is evident that the proposed method shows an improvement of 2 dB in PSNR over wavelet based method at low noise variance values. It can also be seen from the curve that as the value of noise variance increases the improvement in PSNR values reduces from 2 dB for the proposed method. Table 2 shows the comparison of SSIM between wavelet based method and proposed method for gray scale standard Boat image of 256x256 dimensions.

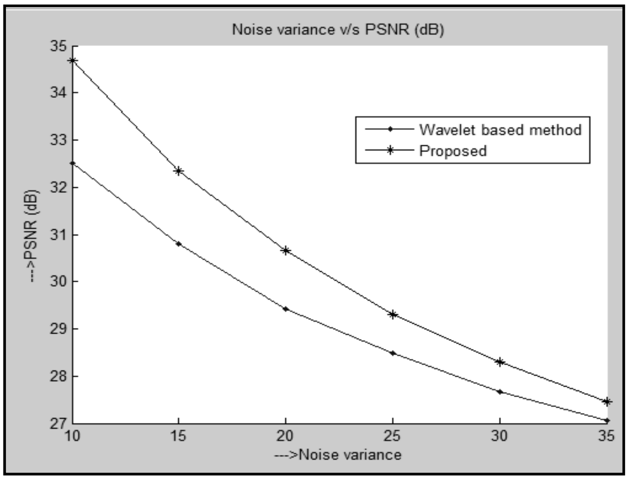

Figure 2 Comparison between wavelet based method and proposed method

The SSIM is higher for the proposed method as compared to wavelet based method. Therefore, the proposed method improves the image quality in terms of both parameters, PSNR and SSIM.

Table 2 SSIM for Boat Image

Image	Noise Level (σ)	SSIM	
		Wavelet Based Denoising Method [1]	Proposed Method
Boat Image (256 x256)	10	0.86	0.98
	15	0.82	0.97
	20	0.79	0.94
	25	0.76	0.93
	30	0.73	0.86
	35	0.71	0.77

Figure 3 shows Simulation results for Standard Boat Image. Figure 3 (a) shows a noisy standard Boat image which is corrupted due to Gaussian noise. Figure 3 (b) shows a denoised standard Boat image with Db4 wavelet.

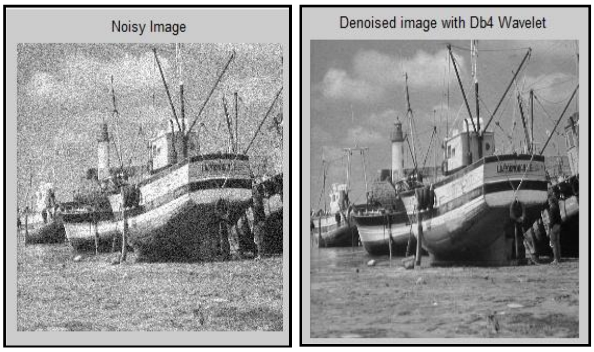

Figure 3 Simulated results for Standard Boat Images (a) Noisy Standard Boat Image (b) Denoised Standard Boat image with Db4 Wavelet

Table 3 shows the value of PSNR and SSIM for Kidney US image corrupted at different noise levels of Gaussian Noise for proposed method.

Figure 4 shows Simulation results for Kidney US Images. Figure 4 (a) shows a noisy Kidney US image which is corrupted due to Gaussian noise. Figure 4 (b) shows a denoised image with Db4 wavelet.

Table 3 PSNR for Kidney Image

Image	Noise Level (σ)	Proposed Method	
		PSNR (dB)	SSIM
Kidney Ultrasound Image (193x256)	10	31.95	0.99
	15	29.60	0.97
	20	27.84	0.95
	25	26.18	0.93
	30	24.80	0.91
	35	23.74	0.89

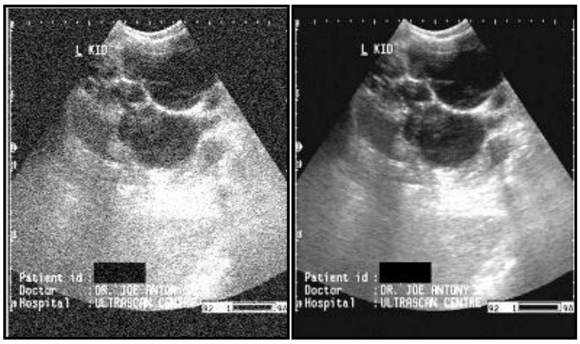

Figure 4 Simulated results for Kidney Ultrasound Images (a) Noisy Kidney Ultrasound Image (b) Denoised Kidney Ultrasound image with Db4 Wavelet

IV. Conclusion

In this work simulation results are presented for gray scale standard Boat image and real Kidney US image. PSNR and SSIM values are obtained for gaussianly corrupted images at different noise variances. It can be concluded from the obtained results that the proposed method is quite effective and lead to the improvement of parameters PSNR and SSIM.

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