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# Image De-Noising Using Modified Bayes Algorithm

KEYWORDS


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**ABSTRACT** *Ultrasound images are tainted with speckle noise. Lately the wavelet transform has been drawing much devotion used for image denoising. Image de-noising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. The research work in this paper comprises of developing a modified bayes thresholding which yields enhanced performance both in visual effects and SNR measurements when compared with conventional bayes while retaining background information. Simulated results show that the proposed bayes thresholding exhibits much better response to remove Speckle noise*

## INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, and computed tomography as well as in areas of research and technology such as geographical information systems and astronomy. Datasets 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 steps [1] to be taken apply an efficient denoising technique to compensate or such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and causes blurring of the images. Noise modeling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation.

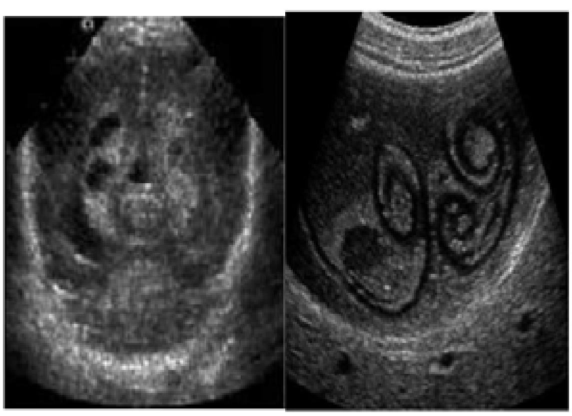

**Fig 1.1: Noisy ultrasound images**

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 [1]. Image De-noising is used to [2] produce good estimates of the original image from noise observations. The restored image should contain less noise than the observations while still keep sharp transitions (i.e edges).Suppose an image is corrupted by the additive noise .Then like:- Where are independent identically distributed Gaussian random variable with zero mean and variance. [3]

## CLASSIFICATION OF DENOISING ALGORITHMS

There are two basic approaches to image denoising,

- Spatial filtering methods
- Transform domain filtering methods.

## SPATIAL FILTERING

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters [1].

## NON-LINEAR FILTERS

With non-linear filters, the noise is removed 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. [4] [5]

## 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. [6].

## TRANSFORM DOMAIN FILTERING

The transform domain filtering methods can be sub divided according to the choice of the basic functions. The basic functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular [3].

## SPATIAL-FREQUENCY FILTERING

Spatial-frequency filtering refers use of low pass filters using Fast Fourier Transform (FFT). In frequency smoothing methods the removal of the noise is achieved by designing a frequency domain filter and adapting a cut-off frequency when the noise components are de correlated from the useful signal in the frequency domain. [7].

## WAVELET TRANSFORM

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The wavelet transform (WT) a powerful tool of signal and image processing that have been successfully used in many scientific fields such as signal processing, image compression, computer graphics, and pattern recognition. A speckle suppression method for medical ultrasound image based on data fusion and wavelet transform are as flow:-

Logarithmic transform was carried out to the medical ultrasound image. Multiplicative noises were transformed into additive ones.

Two original images from the same source with different noises were decomposed each by wavelet transform. For low frequency image, the new approximation coefficients were obtained by the weighted mean value of the approximation coefficients in two original images. For high frequency sub-band images, the new coefficients were selected by those coefficients with bigger absolute values in two original images. The details in high frequency image were reserved furthest.

The denoised image was reconstructed by the inverse wavelet transform using the new wavelet coefficients and the exponential transform was processed.

### DISCRETE WAVELET TRANSFORM

Resolution has been normally referred as an important feature of an image. Images are being managed in order to obtain more improved resolution. One of the generally used methods for image resolution improvement is Interpolation. Interpolation has been broadly used in many image processing applications such as facial rebuilding, various description coding [8], and fabulous resolution. There are three well identified interpolation methods, namely adjacent neighbor interpolation, bilinear interpolation +n, and bicubic interpolation. Image resolution improvement in the wavelet domain is a relatively new research topic and in recent times many new algorithms have been planned [9]. Discrete wavelet transform (DWT) is one of the recent wavelet transforms used in image processing. [8] [10]

**Algorithm for Denoising Bases on New Threshold**

We can summarize the process Bayes Shrink, proposed bayes shrink as

**Step 1**

Input Noisy ultrasound image.

**Step 2**

Perform Multiscale decomposition of the image corrupted by Speckle noise using wavelet transform.

**Step 3**

Estimate the noise variance $\sigma^2$ using equation

$$K = f * \frac{\sqrt{\log(L_k)}}{\max(\sigma)}$$

**Step 4**

For each scale compute the scale parameter K. from equation

$$\sigma^2 = \left(\frac{median(|Y_{ij}|)}{0.6745}\right)^2 \quad Y_{ij} \in \quad subband\ HH$$

**Step 5**

For each suhband (except the lowpass residual).

- Compute the standard deviation using equation

$$\sigma_x = \sqrt{\max(\sigma_y = \sigma^2, 0)}$$

- Compute threshold T using equation (8) if subband variance is greater than noise variance, otherwise set T to maximum coefficient of the subband.

**Step 6**

Invert the multiscale decomposition to reconstruct the denoised image.

### IMPLEMENTATION

Wavelet shrinkage is a method of removing noise from images in wavelet shrinkage, an image is subjected to the wavelet transform, the wavelet coefficients are found, the components with coefficients below a threshold are replaced with zeros, and the image is then reconstructed. In particular, the bayes shrink method has been attracting attention recently as an algorithm for setting different thresholds for every subband. Here subbands are frequently bands that differ from each other in level and direction. The BS method is effective for images including noise.

Bayes Shrink was proposed by Chang, Yu and Vetterli. The goal of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink. The Bayes threshold, is de-

$$T_B = \frac{\sigma^2}{\sigma_s}$$

The observation model is expressed as follows

W=S+N

Here W is the wavelet transform of the degraded image, S is the wavelet transform of the original image, and N denotes the wavelet transform of the noise components following the

W(x,y)=S(x,y)+N(x,y)

$\sigma_w^2$ is computed as

$$\sigma_w^2 = \sigma_s^2 + \sigma^2$$

The variance of the signal, is computed as

With this we can compute the bayes threshold.

### RESULTS

Our test comprises of an ultrasound image Neck, Chest and Stomach of size (256×256). The kind of noise is Speckle with Standard Deviation respectively and images used are in bitmap map format i.e. having an extension of .bmp files.

**Table 1.1: SNR comparison of noisy & denoised image with Bayes & Modified Bayes Thresholding.**

| Images Bitmap (.bmp) | Bayes Thresholding Noisy Image (Speckle Noise) [11] | Proposed Thresholding Noisy Image (Speckle Noise) | Bayes Thresholding Denoised Image (Speckle Noise) [11] | Proposed Thresholding Denoised Image (Speckle Noise) |
|---|---|---|---|---|
| Neck: ($\sigma$ = 0.0875) | 21.03 | 21.1282 | 18.04 | 22.4612 |

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|---|---|---|---|---|
| Chest: $(\sigma = 0.0815)$ | 21.45 | 21.7671 | 19.49 | 23.3653 |
| Stom-ach: $(\sigma = 0.0983)$ | 21.03 | 21.0543 | 16.18 | 21.1800 |

Speckle noise is supplementary added to original image. Our simulation results with modified Bayes threshold are compared with Bayes Thresholding [11] used for denoising.

Simulation results shows that proposed modified Bayes Thresholding outperforms the conventional Bayes Thresholding.

SNR measurements of simulated results for denoised images are compared in Table 1.1. When speckle noise is added to the results shows that proposed thresholding efficiently denoised the noisy image and hence thereby restores the detailed features of original image.

Simulation results for denoising of ultra sound image of Neck is shown in below Fig. 1.2. Original Image of neck is in bitmap format i.e. with .bmp extension. Speckle Noise with Standard Deviation is added to it which will give noisy image as shown in below figure. Then by applying proposed modified Bayes thresholding it yields better denoised image having SNR value 22.4612 when compared with the SNR 18.04 of conventional Bayes thresholding.

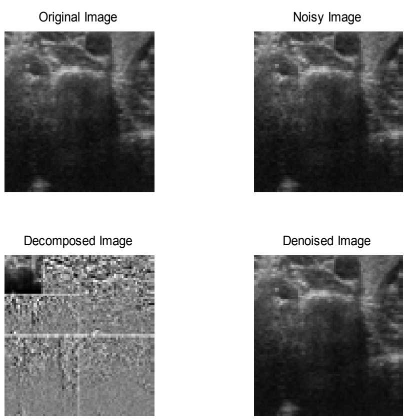


**Figure 1.2: De-noised ultrasound image of Neck using Modified Bayes Thresholding.**

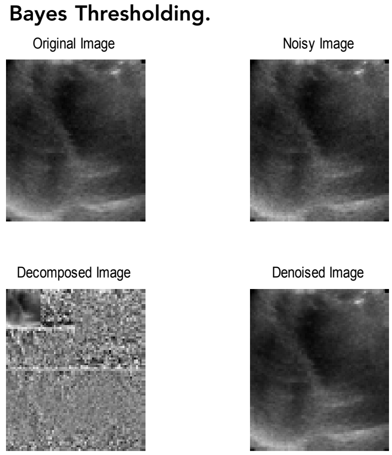


**Figure 1.3: De-noised ultrasound image of Chest using Modified Bayes Thresholding**

Simulation results for denoising of ultra sound image of Chest is shown in below Fig. 1.3. Original Image of neck is in bitmap format i.e. with .bmp extension. Speckle Noise with Standard Deviation is added to it which will give noisy image as shown in below figure. Then by applying proposed modified Bayes thresholding it yields better denoised image having SNR value 23.3653 when compared with the SNR 19.49 of conventional Bayes thresholding.

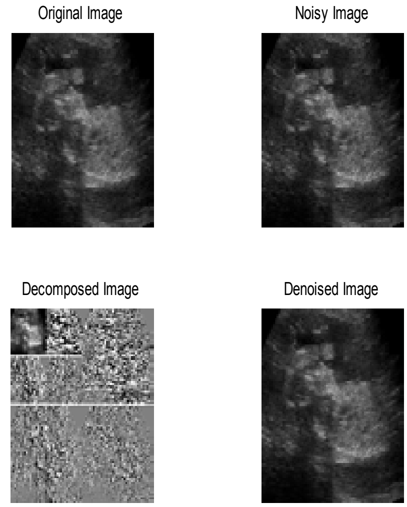


**Figure 1.4: De-noised ultrasound image of Stomach using Modified Bayes Thresholding.**

Simulation results for denoising of ultra sound image of Stomach is shown in below Fig. 1.4. Original Image of neck is in bitmap format i.e. with .bmp extension. Speckle Noise with Standard Deviation is added to it which will give noisy image as shown in below figure. Then by applying proposed modified Bayes thresholding it yields better denoised image having SNR value 21.1800 when compared with the SNR 16.18 of conventional Bayes Thresholding

**CONCLUSION**

In this Paper, a modified bayes thresholding is developed for denoising of ultrasound images in the DWT domain, has been implemented. Simulated results show that the proposed bayes thresholding exhibits much better response to remove Speckle noise efficiently than the conventional Bayes Thresholding. It yields much enhanced performance both in visual effects and SNR measurements while retains background information.

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