Medical Image Denoising Using Sub Band Adaptive Thresholding Techniques Based on Wavelet 2D Transform

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Abstract

Medical images are corrupted by noises during its transmission and acquisition process. Noise reduction has been a traditional problem in image and signal processing. Medical images generally contains minute information about heart, brain, nerves etc therefore wrong diagnosis might not rescue the patient from harmful effects. In this paper we proposed an approach for image denoising based on wavelet 2D transform using adaptive thresholding technique. The proposed technique estimates the threshold value and decomposition level for an image. In this an additive white Gaussian noise is added to image and forward wavelet transform is applied on noisy image. After this wavelet coefficients are threshold and inverse wavelet transformation is performed to restore the original image. The proposed method reduce the noise from image more effectively. The MATLAB result shows that adaptive thresholding method is better than the other traditional methods as it minimize the mean square error (MSE). Bayes soft thresholding obtained better results in terms of PSNR value.

Keywords: Image processing, additive white Gaussian noise, wavelet transform, Image denoising, Adaptive thresholding

1. Introduction

Medical image denoising is a procedure in image processing which aims at removal of noise from an image. Distinct type of noises like additive Gaussian noise, multiplicative speckle noise and artifacts in different imaging modalities degrade the image quality [2]. Such disturbance severely affects the human interpretation as well as the accuracy of computer assisted methods in case of medical imaging. Computer- aided analysis and quantitative measurements become difficult and unreliable due to poor image quality therefore the denoising and enhancement of the images become major requirements for many applications. The wavelet transform is an important tool for this problem due to its energy compaction property [5]. The wavelet transform is better than Fourier transform because it gives frequency representation of raw signal at any given interval of time, but Fourier transform gives only the frequency- amplitude representation of the raw signal, but the time information is lost. So we cannot use the Fourier transform where we require time as well as frequency information at the same time [2]. Wavelet transform is basically a mathematical functions that cut up data into different frequency components. The fundamental idea behind wavelet transform is to analyze the signal at different scales or resolutions, which is called multiresolution. The important feature of wavelet transform is it allows multiresolution decomposition. On this basis the proposed paper put forward an advanced technique of image denoising based on wavelet thresholding. The thresholding of wavelet coefficients in the transformed domain has been done using Visu shrink, Sure shrink and Bayes shrink. An approach which is adaptive in sub band of wavelet decomposition has been devised in this paper. The important parameter of wavelet decomposition is the decomposition level. The input image is trained using the additive

white Gaussian noise with different noise density and then applied to the proposed technique. The results show that the proposed method outperforms   in terms of PSNR value.

2. Wavelet Transform

Discrete wavelet transform (DWT) decompose signals into sub bands with minor bandwidths and lower sample rates explicitly Low-Low (LL), Low-High (LH), High-Low(HL), and High-High (HH). With these four sub-bands from one level of transform - first low-pass sub-band having the common estimate of the foundation image called LL sub band and three high pass sub bands that develop image details across unusual directions - HL represents horizontal, LH represent vertical and HH represents diagonal details. After sub-band decomposition high frequency components are obtained used for the detailed analysis of image to yield enhancement to rebuild the image from its 2-D DWT subordinate present images (LH, HL, HH) the particulars are recombined with the low pass estimate with up sampling and convolution through the particular synthesis filters. Figure 1 (a) shows the original disease image, Figure 1(b) shows decomposed image into sub bands at level 5.
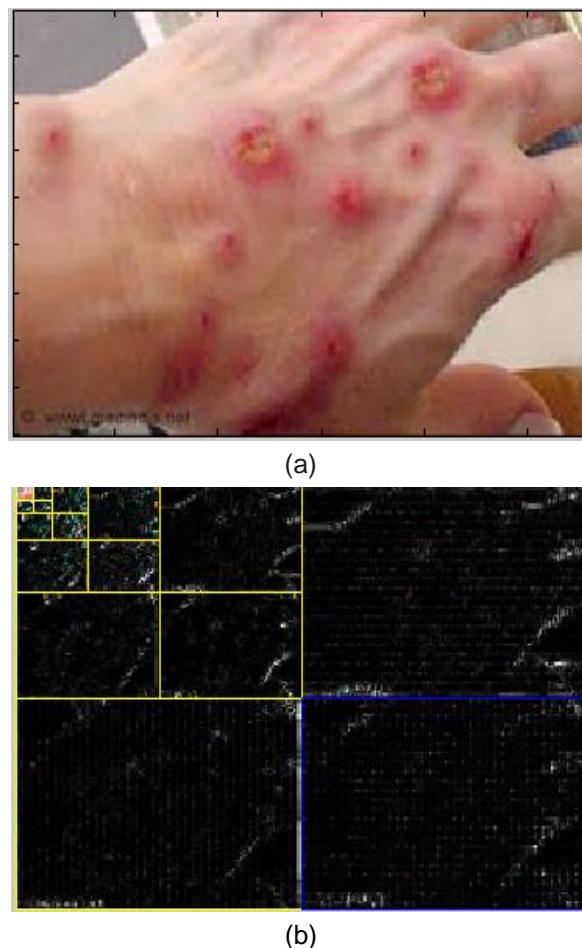

(a)

(b)

Figure 1. (a) Original Disease Image, (b) Decomposition at level 5

3. Wavelet Thresholding

Let f= {fij, i, j=1, 2 ...M} denotes a M x M matrix of original image to be recovered and M is some integer power of 2. During the transmission, the image f is corrupted by

independent and identically distributed (i.i.d.) zero mean, white Gaussian noise nij with standard deviation σ *i.e.*, nij ~ N (0, σ^2) and at the receiver end, the noisy observation gij=fij+nij is obtained. The goal is to estimate the image f from the noisy observations gij such that the Mean Square Error (MSE) is minimum. To achieve this gij is transformed into wavelet domain, which decomposes the gij into different sub bands, which separates the image into so many frequency bands. The small coefficients in the sub bands are dominated by noise, while coefficients with large absolute value carry more image information than noise. Replacing noisy coefficients (small coefficients below certain value) by zero and an inverse wavelet transform may lead to reconstruction that has reduced noise contents. Normally Hard Thresholding and Soft Thresholding techniques are used for such denoising process. Hard and Soft thresholding [3] with threshold λ are defined as follows.

$$\text{Hard thresholding:} \quad y = x \text{ if } | x | > \lambda \qquad (1)$$

$$y = 0 \text{ if } | x | < \lambda$$

$$\text{Soft thresholding:} \quad y = \text{sign} (x) (| x | - \lambda) \qquad (2)$$

4. Shrinkage Methods of Denoising

A. Visu Shrink.

Visu Shrink is thresholding by applying universal threshold [3] proposed by Dohono and Johnston. This threshold is given by:

$$\lambda = \sigma * \sqrt{(2 * \log M)} \qquad (3)$$

Where, σ is the noise variance of AWGN and M is the total number of pixels in an image. It is proved in [1] that a large fraction of any M number of random data array with zero mean and variance, σ will be smaller than the universal threshold, λ with very high probability; the probability approaching 1 as M increases. Thus, with high probability, a defined and pure noise signal is estimated as being identically zero. Therefore, for denoising applications, Visu Shrink is found to yield a highly smoothed estimate. This is because the universal threshold is derived under the constraint that with high probability, the estimate should be at least as smooth as the signal. So the λ tends to be high for large values of M, thereby killing many signal coefficients along with the noise. Thus, the threshold does not acquire well to discontinuities in the signal.

B. Sure Shrink.

Sure Shrink [4] is an adaptive thresholding method where the wavelet coefficients are treated in level-by-level fashion. In each level, when there is information that the wavelet representation of that level is not less or sparse, a threshold that minimizes Stein's unbiased risk estimate (SURE) is applied. Sure Shrink is used for suppression of additive noise in wavelet-domain where a threshold λ SURE is employed for denoising.

The threshold parameter λ SURE is expressed as:

$$\lambda = \arg_{m \geq 0} \min SURE(m, X) \qquad (4)$$

Where the stein's unbiased risk is minimized in eqn5,

$$SURE(m, X) = d - 2\{i : X_i \leq m\} + \sum_{i=1}^{d} \min(X_i, m)^2 \qquad (5)$$

where X is the coefficients of the sub band X and d is the number of coefficients in the sub band. This optimization is straight forward and yields result which has smooth images. The results obtained are better than Visu Shrink.

C. Bayes Shrink

In BayesShrink [5], an adaptive data-driven threshold is used for image denoising. The wavelet coefficients in a sub-band of an image can be represented effectively by a Generalized Gaussian distribution (GGD). Thus, a threshold is derived in a Bayesian framework as:

$$\lambda = \frac{\sigma_{noise}^2}{\sqrt{max(\sigma_Y^2 - \sigma_{nois}^2)}} \tag{6}$$

where σ_{noise}^2 is the estimated noise variance of AWGN by robust median estimator and σ_Y^2 is the estimated signal standard deviation in wavelet-domain. The robust median estimator is stated as:

$$\sigma_{noise} = \mathbf{medain}(Y_{i,j})/0.6745 \tag{7}$$

This estimator is used when there is no a priori knowledge about the noise variance.

5. Results

Results are presented for medical image. All these images are of uint 8-bit gray scale images having dimensions 256 X 256. The entire medical image is in png format. For the purpose of decomposition 2-D is used at level 5. Peak signal to noise ratio (PSNR) is given as:

$$\mathbf{PSNR(db)} = 10 * \mathbf{log_{10}}(255^2 / \mathbf{MSE}) \tag{8}$$

Mean square error (MSE) is given as:

$$\mathbf{MSE} = 1/(M * N) * \sum_{m,n}[\mathbf{I_1}m,n - \mathbf{I_2}m,n]^2 \tag{9}$$

where M,N are the dimensions of the input images respectively. I_1, I_2 are the original and denoised images. PSNR and MSE are the parameters for objective evaluation of denoised image. Images are shown for different shrinkage methods using hard and soft thresholding techniques. The MATLAB results for the shrinkage method visu shrink, sure shrink, bayes shrink are implemented and images are obtained on the basis of proposed technique.
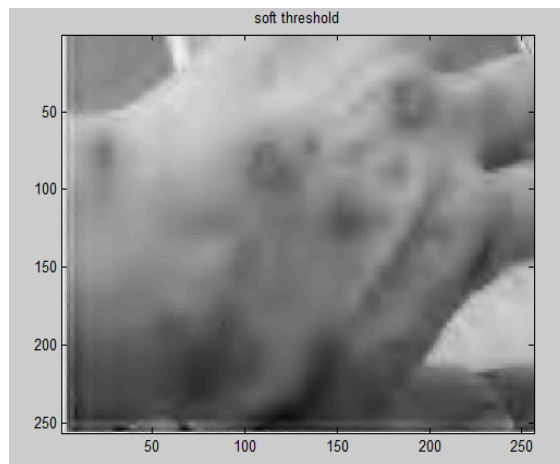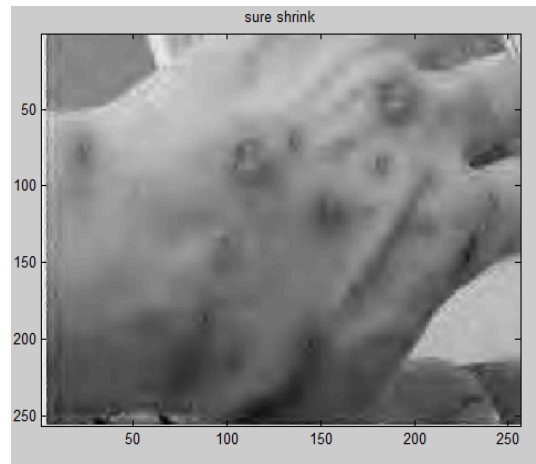
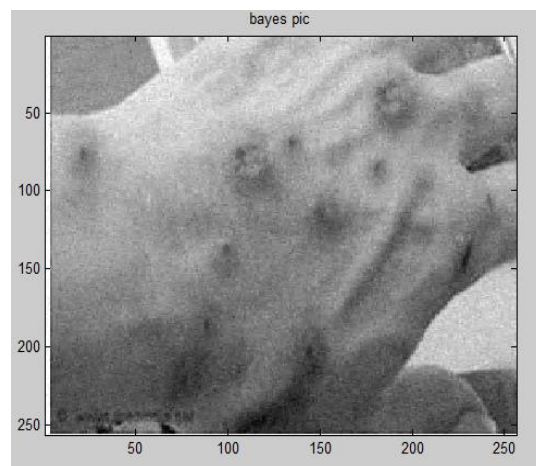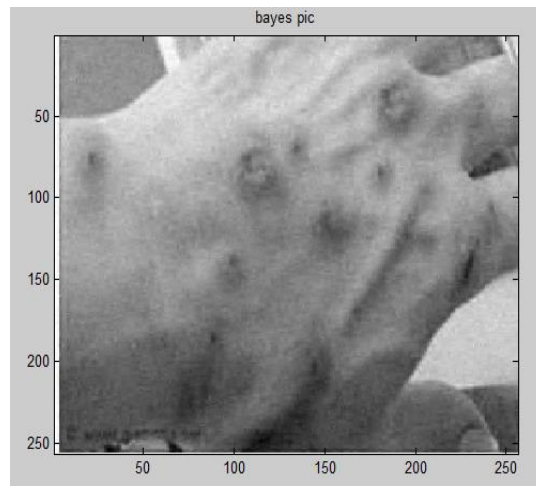The MATLAB results are as shown:
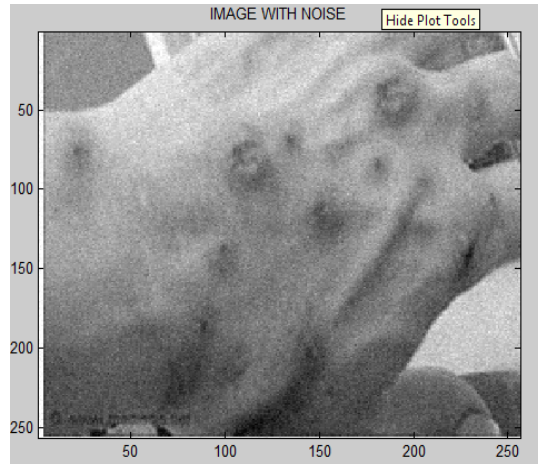
(a)
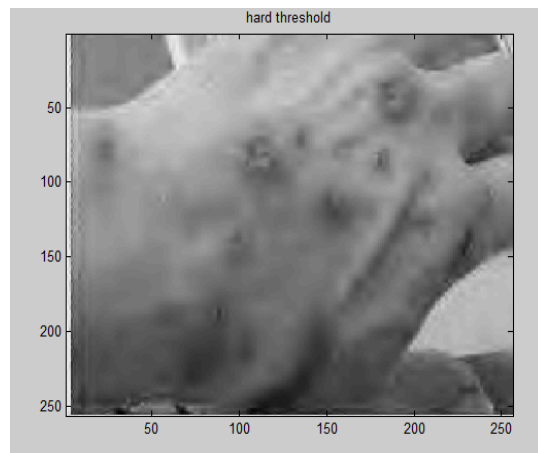
(b)

(c)

(d)

(e)

(f)

Figure 2. Denoised Images (a) Noisy Image (b) Visu Hard Shrink (c) Visu Soft Shrink (d) Sure Shrink (e) Bayes Hard Shrink (f) Bayes Soft Shrink

The plots are obtained for peak signal to noise ratio (PSNR) and mean sure error (MSE) which is shown in Figure 3 and Figure 4 respectively.
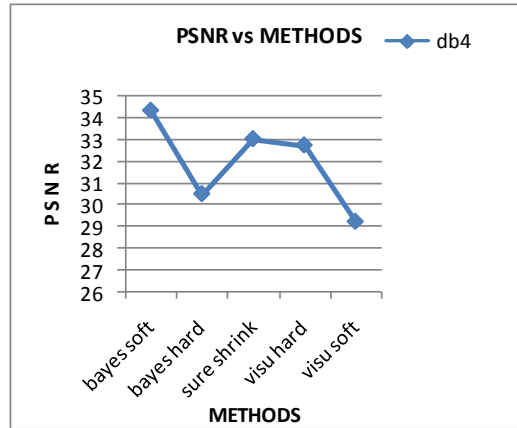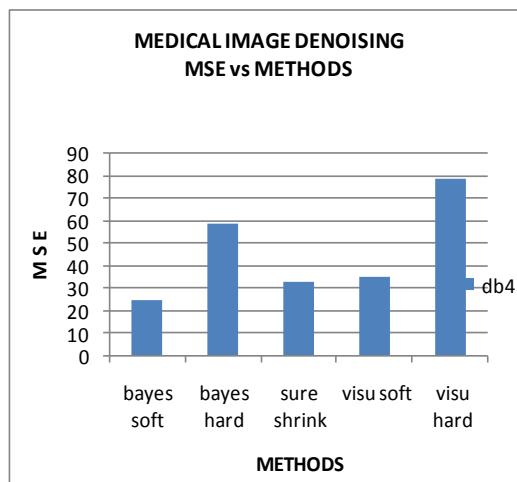
Figure 3. Plot for PSNR Values

Figure 4. Plot for MSE v/s Different Methods

6. Conclusion

Image denoising is an important feature of image and signal processing. Noise is suppressed by denoising the image using wavelet thresholding. The results are obtained by different methods of wavelet thresholding Visu shrink, Sure shrink, Bayes shrink. It is shows that mean square error is reduced to greater extent and the peak signal to noise ratio is maximized. Results obtained determines that the proposed method suppresses the Gaussian noise. Bayes shrink produces better restoration results in terms of PSNR and visual effects.

Acknowledgment

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