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Comparative Study of Image Denoising Algorithms in Digital Image Processing

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Abstract: This paper proposes a basic scheme for understanding the fundamentals of digital image processing and the image denising algorithm. There are three basic operation categorized on during image processing i.e. image rectification and restoration, enhancement and information extraction. Image denoising is the basic problem in digital image processing. The main task is to make the image free from Noise. Salt & pepper (Impulse) noise and the additive white Gaussian noise and blurredness are the types of noise that occur during transmission and capturing. For denoising the image there are some algorithms which denoise the image.

Index Terms: Visu Shrink method, Sure Shrink method, Base Shrink thresholding model

INTRODUCTION

Digital image processing is the branch of science which is related to the image. Which represent two-dimensional image as a finite set of picture elements or pixels? Pixel values represent gray levels, colours, heights, opacities etc.

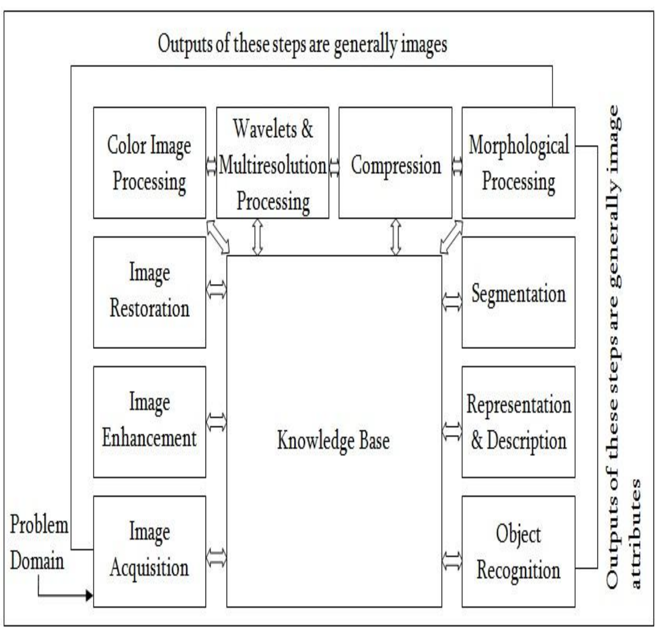


Figure (1.1) Different studies in digital image processing

Digital image processing is the branch of science which is related to the image. It further is divided in many parts. Which is shown in the fig 1.1.this paper is based on the Denoising algorithm. Further these algorithms are of different types. A Denoising technique is used when image get corrupted or in other words image get noise in it and its visualization is get effected with formation of false edges. so here we discuss the different algorithm and technique to remove the noise from image. For getting the better result from shrinkage approaches is blended with other operations. New parameters can be used for the evaluation of Denoising techniques. Future, Gaussian-based model can be used to analyze and compared the image characteristics.

1.1 Image Denoising Algorithms

The implementation of various image denoising algorithm based on wavelet transform have been described in this chapter for gray scale image.

1.1.1 Image Denoising Algorithms for Gray-Scale Image

Image denoising by using different thresholding techniques are described under the section given below. These all algorithms are based on wavelets and thresholding schemes.

1.1.2 Universal Thresholding.

$$Tc = \sigma \sqrt{(2 \log M)} \qquad (1.1)$$

Where Tc is threshold value, M is the data length, σ is the noise variance of data estimated according to Equation Universal thresholding is non-data dependent because it is not inspecting each data statistically. However it is certainly an adaptive threshold method due to parameters such as M and σ in its expression.

1.1.3 Visu Shrink Method

Then soft and hard thresholding is applied to the wavelet detail coefficient using the given threshold. The denoised image is obtained by performing IDWT to the thresholded wavelet coefficients.

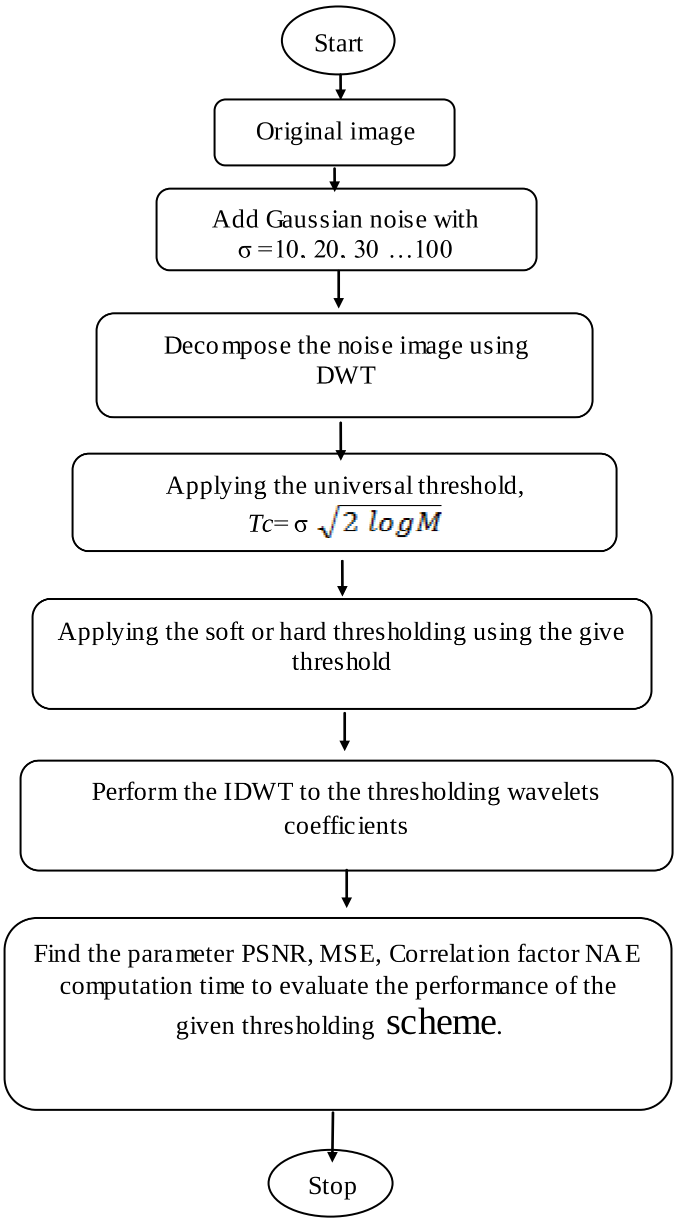


Figure (1.3) Flow chart of Visu Shrink method

1.1.4 Sure Shrink

Sure shrink is an estimate method drive by data. The estimate threshold is than lower that of Visu Shrink and regressively optimal D.L.Donoho suggested choosing the optimal threshold value T by minimizing Sure [6]. The significance of this is that it is possible to transform the original data into its WC, and then attempt to minimize risk in the wavelet domain; doing so will automatically minimize risk in the original domain. In practical situation the risk R(f̂ , f) must be estimated from the data. This method employs an unbiased estimate of risk that is due to Stein called Stein Unbiased Risk Estimator (SURE) [3].

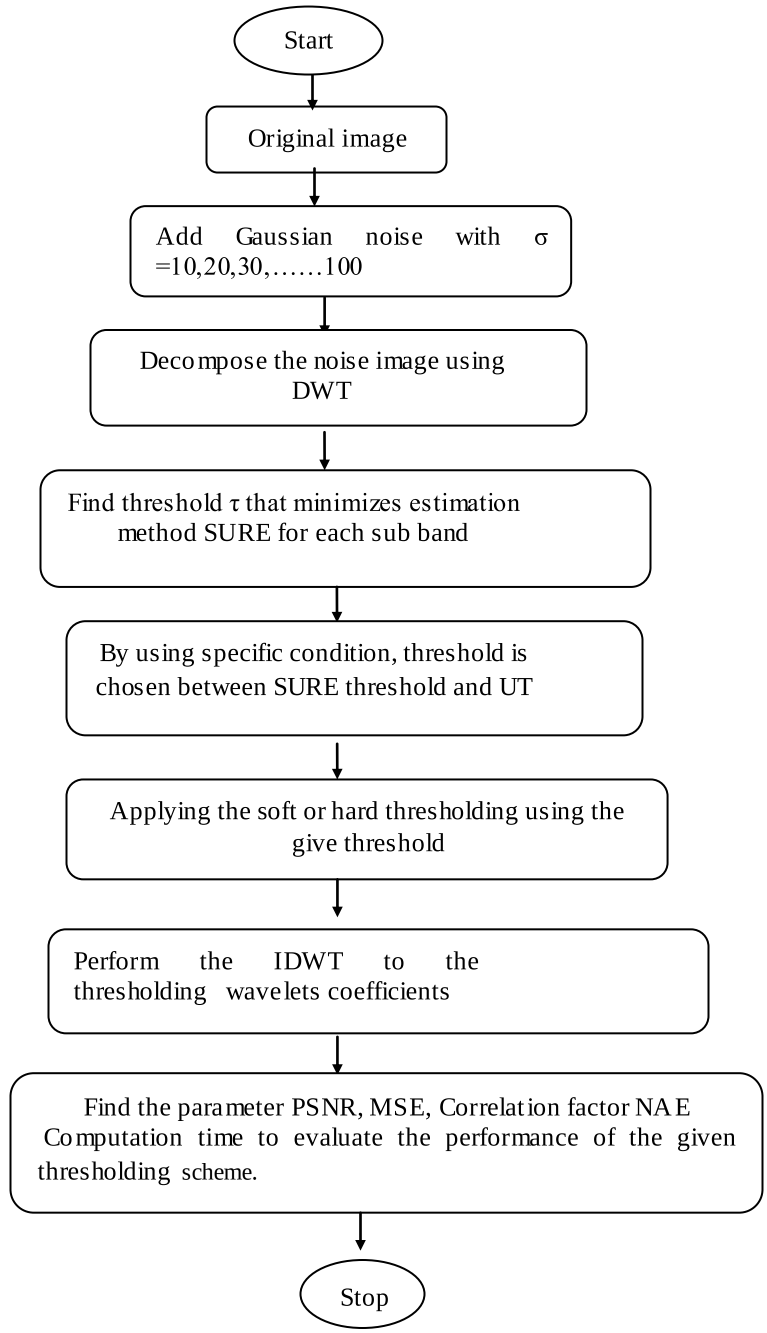


Figure (1.4) Flow chart of Sure Shrink method

T_d^F in dense situation and to T_s in space situation

$$\hat{\mu}(x_i) = \begin{cases} \eta T_d^{F(\cdot)} \\ \eta T_d^{F(\cdot)} \end{cases} \quad (1.2)$$

Where

$$S_d^{\,2} = d^{-1}\sum_i \left(x^2{}_i - 1\right) \quad (1.3)$$

and, $$\eta_d = \log_2(d)^{3/2} \quad (1.4)$$

η being the thresholding operator.

Sure applied to image denoising are First step is to perform WT on the noisy image which corrupted by AWGN. Then SURE thresholding method is applied to wavelet coefficient. The SURE is determined for each sub-band using the equation (1.2), (1.3) and (1.4). Then SureShrink method applied to between SURE threshold and UT. The denoised image is obtained by performing IDWT to the threshold wavelet coefficients.

- Advantages
- Its minimization over a set of denoising automatically provides a near optimal solution.
- SURE based give best result as a output PSNR for images.
- The quality image is moreover characterized by fewer artifacts that the other methods.
- Disadvantage
- Computational time is more than other denoising methods.

1.1.5 Base Shrink Method

Bayesian methods for function estimation with wavelets are different then simple threshold selection, in the sense that new shrinkage functions result from the Bayesian approach, different from either the soft or hard thresholding functions discussed previously. It is seen that Bayesian rule is not a threshold estimator only. It is directly estimating γ k without using soft or hard thresholding for a specific level. The thresholding is driven in a Bayesian framework, and GDD is assumed for the wavelets coefficients in each detail sub-band. The GDD is given by

$$GG_{\sigma_x,\beta}(x) = C(\sigma_x,\beta)\exp\left\{-\left[\alpha(\sigma_x,\beta)|x|\right]^{\beta}\right\} \quad (1.5)$$

Where $-\infty < x < \infty, \sigma_x \rangle 0, \beta \rangle 0$

$$\alpha(\sigma_x,\beta) = \sigma^{-1}{}_x\left[\frac{\Gamma(3/\beta)}{\Gamma(3/\beta)}\right]^{1/2} \quad (1.6)$$

$$C(\sigma_x,\beta) = \frac{\beta.\alpha(\sigma_x,\beta)}{2\Gamma(1/\beta)} \quad (1.7)$$

$\Gamma(t) = \int_0^\infty e^{-u}u^{t-1}du$ is the gamma function

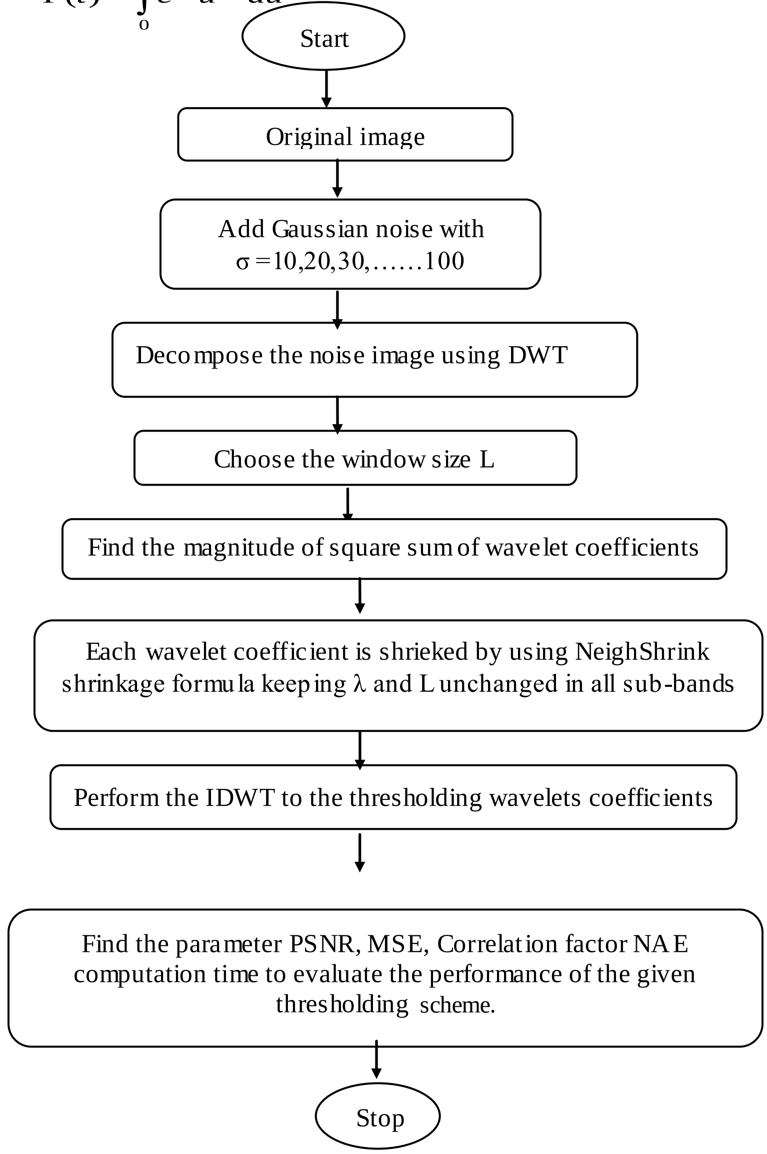


Figure (1.5) Flow chart of BaseShrink thresholding model

The GDD parameters and β needs to be estimated to compute data- driven estimate of ( ).

$$\sigma^2{}_Y = \sigma^2{}_x + \sigma^2 \quad (1.8)$$

Where is the variance of Y.? Since Y is modeled as zero-mean, is found as

$$\sigma^2{}_Y = \frac{1}{n^2 i, \sum_{j=1}^{n} Y_{ij}^{\,2}} \quad (1.9)$$

n × n =size of sub domain. Also, is defined as

$$\sigma^2{}_X = \max\left(\sigma^2{}_Y - \sigma^2, 0\right) \qquad (1.10)$$

Therefore the data driven, sub band-dependent Bayes threshold is given as

$$T_B = \frac{\sigma^2}{\sigma_X} \qquad (1.11)$$

First step is obtained wavelet decomposition on the noise image which is corrupted by AWGN. Then BaseShrink thresholding method is applied to the wavelet coefficient. The threshold is determined using the equation (1.11). The denoised image is obtained by performing IDWT to the thresholded wavelet coefficients. It is found that the BaseShrink perform well.

- **Advantage**
  - It is found that BaseShrink performs better than SureShrink in term of MSE.
  - The reconstruction using BaseShrink is smoother and more visuallyappealing than one obtained using SureShrink.
- **Disadvantage**
  - The rule is close to a thresholding rule because it heavily shrinks small-in-magnitude arguments with minor influence on the larger arguments.

1.1.6 Neigh Shrink method

The WT accomplished by applying the low pass and high pass filter on the same set on low frequency coefficient recursively. That means wavelet is correlated in a small neighborhood.

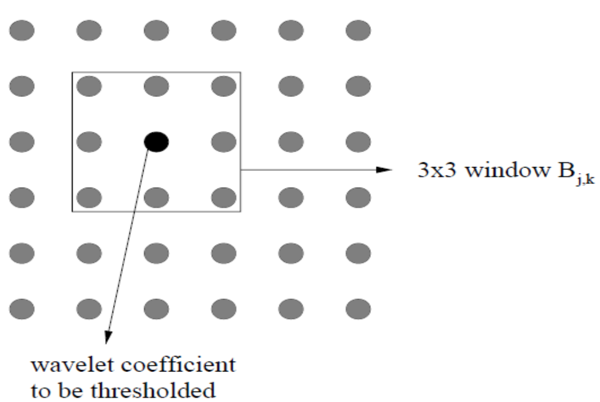
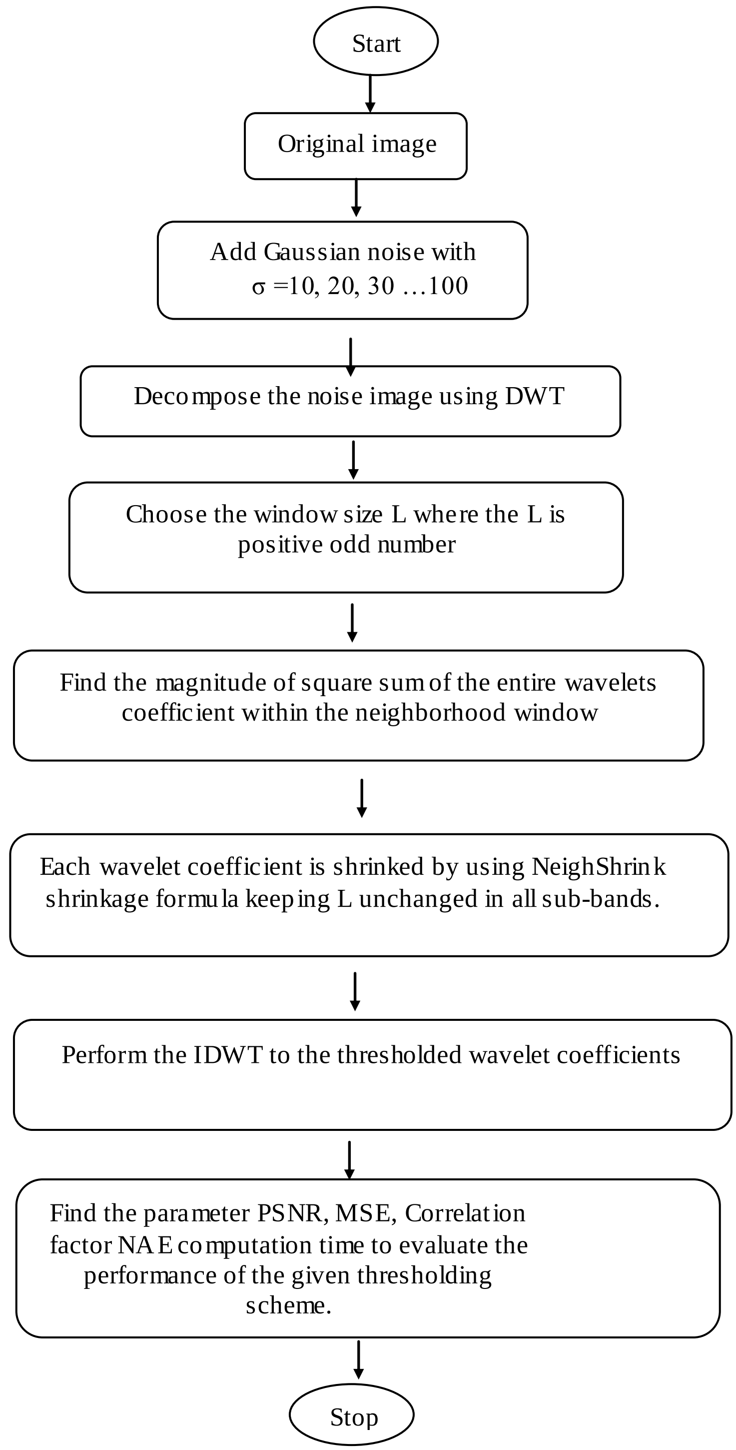


Figure (1.6) An example of the neighborhood window with size 3 × 3.



- **Advantage**
  - It is found that NeighShrink performs better than other interim of PSNR.
  - Computational times is less than other denoising methods.

Conclusion:

To make the PSNR better than the previous method we applied the median filter for coefficient approximation which gives the better result. The only different between above method and proposed method is in wavelets threholding. In the above method, wavelet threholding used is BaseShrink, whereas in proposed method, it is NeighShrink. A signal is decomposed into its frequency sub-band with wavelet decomposition; as the signal is reconstructed back, MF is applied to the approximation sub-band. It is method which integrates MF and NeighShrink threholding. In this method, an image is decomposed in to low- and high- component, and then, MF is applied on the approximation sub-bands and NeighShrink threholding on the detail sub-bands

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