# A Novel Hybrid Filtering Method for Color Image Denoising Using Different Wavelets

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*Abstract*— **Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. In this paper existing denoising algorithms, such as Donoho Soft & Hard Thresholding Denoising, Standard wavelet denoising, Baysian Thresholding denoising, Bayes Shrinkage Denoising, BLS Denoising and our Proposed Method was implement and their comparative analysis has been studied. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise Selection of the denoising algorithm is application dependent. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used. A quantitative measure of comparison is provided by the signal to noise ratio and Mean square error of the image.**

*Keywords*— **Standard wavelet denoising, Baysian Thresholding denoising, Bayes Shrinkage Denoising, BLS Denoising**

## I. INTRODUCTION

Images provide visual representation of the content that is to be examined and allow the users to reflect on them later. They are a powerful data collection medium [1,2] that is stored easily and used indefinitely. With the advent of digital imaging, a whole new set of possibilities have opened up for professional and amateur users. The amateur users can now easily snap, store, edit and share images , while researchers and professional users rely on them to identify areas of interest, scrutinize details and present their findings effectively.

Image Enhancement (IE) transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including (but not limited to) medical imaging, art studies, forensics and atmospheric sciences. It is application specific: an IE technique suitable for one problem might be inadequate for another. For example forensic images/videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. To cater for such an ever increasing demand of digital imaging, software companies have released commercial software's for users who want to edit and visually enhance the images.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. They must be oscillatory (waves) and have amplitudes which quickly decay to zero in both directions. This idea is not new. Approximation using superposition of functions has existed since the early 1800's, when Joseph Fourier discovered that he could superpose sines and cosines to represent other functions. However, in wavelet analysis, the *scale* that we use to look at data plays a special role. Wavelet algorithms process data at different *scales* or *resolutions.* If we look at a signal with a large "window," we would notice gross features. Similarly, if we look at a signal with a small "window," we would notice small features. The result in wavelet analysis is to see both the forest *and* the trees, so to speak.

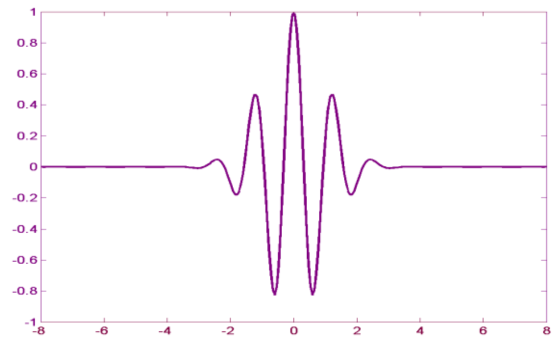



**Fig. 1.1: Morlet mother wavelet**

| | | | | |
|---|---|---|---|---|
| 123 | 125 | 126 | 130 | 140 |
| 122 | 124 | 126 | 127 | 135 |
| 118 | 120 | 150 | 125 | 134 |
| 119 | 115 | 119 | 123 | 133 |
| 111 | 116 | 110 | 120 | 130 |

The wavelet analysis procedure is to adopt a wavelet prototype function, called an *analyzing wavelet* or *mother wavelet (Fig. 1.1).* Temporal analysis is performed with a contracted, high-frequency version of the prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the same wavelet. Because the original signal or function can be represented in terms of a wavelet expansion (using coefficients in a linear combination of the wavelet functions), data operations can be performed using just the corresponding wavelet coefficients. And if you further choose the best wavelets adapted to your data, or truncate the coefficients below a threshold, your data is sparsely represented. This sparse coding makes wavelets an excellent tool in the field of data compression[3].

Wavelet theory represents things by breaking them down into many interrelated component pieces, similar to pieces of jig-saw puzzle; when the pieces are scaled and translated wavelets, this breaking down process is wavelet decomposition or wavelet transform.

Other applied fields that are making use of wavelets include astronomy, acoustics, nuclear engineering, sub-band coding, signal and image processing, neurophysiology, music, magnetic resonance imaging, speech discrimination, optics, fractals, turbulence, earthquake-prediction, radar, human vision, and pure mathematics applications such as solving partial differential equations.

# Present Work

## Background

Filters play a major role in the image restoration process. The basic concept behind image restoration using linear filters is digital convolution and moving window principle. Let $w(x)$ be the input signal subjected to filtering, and $z(x)$ be the filtered output. If the filter satisfies certain conditions such as linearity and shift invariance, then the output filter can be expressed mathematically in simple form as $z(x) = \int w(t)h(x - t)dt$

where $h(t)$ is called the point spread function or impulse response and is a function that completely characterizes the filter. The integral represents a convolution integral and, in short, can be express as

$z = w * h.$

For a discrete case, the integral turns into a summation as

$$z(i) = \sum_{-\infty}^{+\infty} w(t)h(i - t). \quad (4.1)$$

Although the limits on the summation in Equation (4.1) are $\infty$, the function $h(t)$ is usually zero outside some range. If the range over which $h(t)$ is non-zero is ($-k$, $+k$), then the above Equation (4.1) can be written as

$$z(i) = \sum_{i-k}^{i+k} w(t)h(i - t) \,. \qquad (4.2)$$

This means that the output z($i$) at point $i$ is given by a weighted sum of input pixels surrounding $i$ where the weights are given by $h(t)$. To create the output at the next pixel $i$+1, the function $h(t)$ is shifted by one and the weighted sum is recomputed. The total output is created by a series of shift-multiply-sum operations, and this forms a discrete convolution. For the 2-dimensional case, $h(t)$ is $h(t,u)$, and Equation (4.2) becomes

$$z(i, j) = \sum_{t=i-k}^{i+k} \sum_{u=j-l}^{j+l} w(t, u)h(i - t, j - u) \qquad (4.3)$$

Values of $h(t,u)$ are referred to as the filter weights, the filter kernel, or filter mask. For reasons of symmetry $h(t,u)$ is always chosen to be of size $m \times n$ where $m$ and $n$ are both odd (often $m$=$n$). In physical systems, the kernel $h(t,u)$ must always be non-negative which results in some blurring or averaging of the image. If the coefficients are alternating positive and negative, the mask is a filter that returns edge information only.

The narrower the $h(t,u)$, the better the system in the sense of less blurring. In digital image processing, $h(t,u)$ maybe defined arbitrarily and this gives rise to many types of filters. The weights of $h(t,u)$ may be varied over the image and the size and shape of the window can also be varied. These operations are no longer linear and no longer convolutions. They become moving window operations. With this flexibility, a wide range of linear, non-linear and adaptive filters may be implemented.

**Median Filter**

A median filter belongs to the class of nonlinear filters unlike the mean filter. The median filter also follows the moving window principle similar to the mean filter. A 3× 3, 5× 5, or 7× 7 kernel of pixels is scanned over pixel matrix of the entire image. The median of the pixel values in the window is computed, and the center pixel of the window is replaced with the computed median. Median filtering is done by, first sorting all the pixel values from the surrounding neighbourhood into numerical order and then replacing the pixel being considered with the middle pixel value. Note that the median value must be written to a separate array or buffer so that the results are not corrupted as the process is performed. Figure 4.1 illustrates the methodology.

Neighborhood values:

115,119,120,123,124,125,126,127,150

Median value: 124

The central pixel value of 150 in the 3×3 window shown in Figure 4.1 is rather unrepresentative of the surrounding pixels and is replaced with the median value of 124. The median is more robust compared to the mean. Thus, a single very unrepresentative pixel in a neighbourhood will not affect the unrepresentative pixel in a neighbourhood will not affect the median value significantly.

Since the median value must actually be the value of one of the pixels in the neighbourhood, the median filter does not create new unrealistic pixel values when the filter straddles an edge. For this reason the median filter is much better at preserving sharp edges than the mean filter. These advantages aid median filters in denoising uniform noise as well from an image.

**Proposed Method**

Our method is explain with the help of an flow chart which is shown below . In this method firstly a color image is taken (all the images are of 512x512 pixel size) which will be shown as original image at the end of program using imshow command .

**Proposed Algorithm**

The proposed algorithm is explained as follow

Step1: Take a color image( for uniformity all images are taken 512x512 pixel)

Step2: Apply one type of noise at a time to obtain an noisy images ( Gaussian, salt & pepper, speckle noise is used in the thesis )

Step3: Bifurcate the noisy image into three images one have R component, second having G components and third having B component.

Step4: Calculate Horizontal, Vertical and Diagonal Co-efficient of R,G & B components of bifurcated image.

Step5: Apply horizontal, Vertical & Diagonal shrinkage using Alpha,Beta & Lambda predefined variables & delta function defined separately.

Step6: Reconstruction of wavelet decomposition is done.

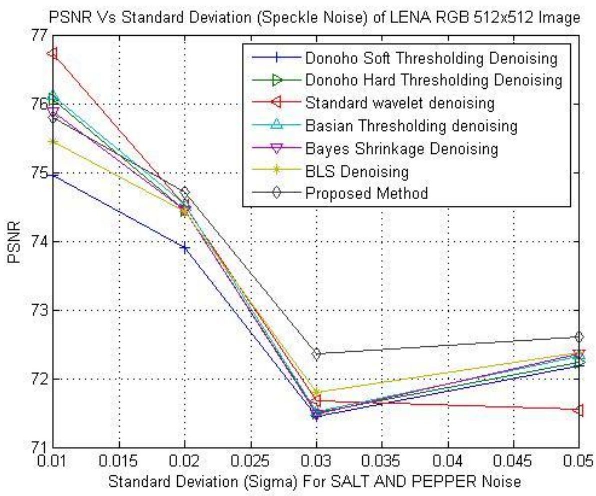
**Results & Discussions**

The proposed algorithm is tested on standard colour image namely Lena . The algorithm is applied using performance indices (namely PSNR) at different noise variance. Along with these comparative studies are represented in this chapter the results are shown in Figure: with the help of MATLAB 7.0 [....] and Table:1.0

| Variance | Donoho Soft Thresholding | Donoho Hard Thresholding | Standard Wavelet Thresholding | Basian Thresholding | Bayes Shrinkage Denoising | BLS Denoising | Proposed Method. |
|---|---|---|---|---|---|---|---|
| **Salt & Peepers Noise** | | | | | | | |
| V=0.1 | 66.6634 | 63.5883 | 63.4796 | 63.8777 | 63.9121 | 68.6322 | 79.2958 |
| V=0.2 | 69.0958 | 64.7576 | 63.336 | 65.553 | 66.6293 | 67.4898 | 73.8283 |
| V=0.3 | 67.6204 | 67.5709 | 66.5089 | 67.5887 | 67.6161 | 67.3668 | 68.1434 |
| V=0.4 | 64.5033 | 64.5033 | 64.4337 | 64.5033 | 64.4774 | 67.4774 | 64.8779 |
| **Zero-mean Gaussian white noise** | | | | | | | |
| V=0.01 | 75.5413 | 75.7257 | 76.1371 | 75.7336 | 75.6689 | 76.2252 | 76.9548 |
| V=0.02 | 74.2667 | 74.2667 | 74.3021 | 74.2719 | 74.253 | 74.5142 | 75.1974 |
| V=0.03 | 73.2512 | 73.2661 | 73.1167 | 73.269 | 73.2641 | 73.3742 | 74.0613 |
| V=0.04 | 71.8032 | 71.804 | 71.5141 | 71.8046 | 71.8045 | 71.797 | 72.4938 |
| **Speckle Noise** | | | | | | | |
| V=0.01 | 75.5413 | 75.7257 | 76.1371 | 75.7336 | 75.6689 | 76.2252 | 76.9548 |
| V=0.02 | 74.2667 | 74.2667 | 74.3021 | 74.2719 | 74.253 | 74.5142 | 75.1974 |
| V=0.03 | 73.2512 | 73.2661 | 73.1167 | 73.269 | 73.2641 | 73.3742 | 74.0613 |
| V=0.04 | 71.8032 | 71.804 | 71.5141 | 71.8046 | 71.8045 | 71.797 | 72.4938 |

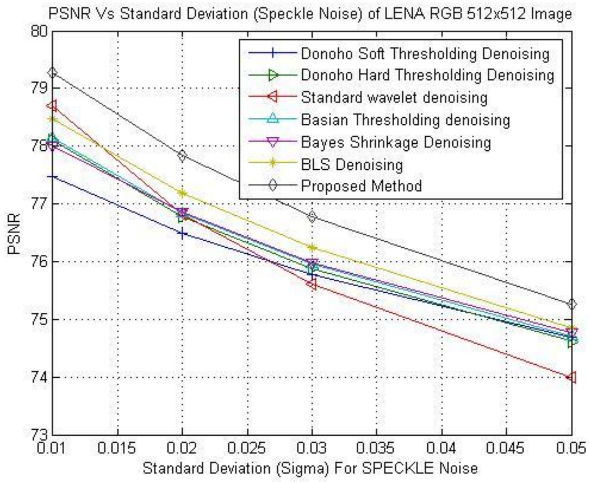
**Noise Type: Salt & pepper**

**1.1** PSNR (in db) Vs Standard deviation(σ) Factor for Lena (512x512) image**:**



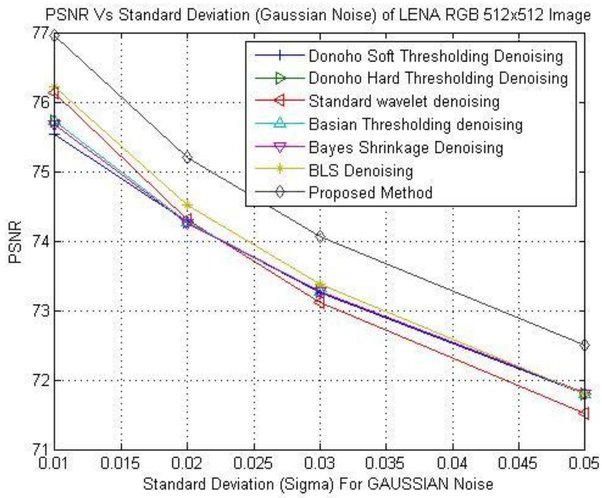
**Noise Type: Speckle noise**

**1.2** PSNR (in db) Vs Standard deviation(σ) Factor for Lena (512x512) image




**Noise Type: Gaussian noise**

**1.3** PSNR (in db) Vs Standard deviation(σ) Factor for Lena (512x512) image:




**Conclusion & Future Work**

From the experimental and mathematical results it can be concluded that for salt and pepper noise, the median filter is optimal compared to mean filter and LMS adaptive filter. It produces the maximum SNR for the output image compared to the linear filters considered. The LMS adaptive filter proves to be better than the mean filter but has more time complexity. From the output images shown in Chapter 5, the image obtained from the median filter has no noise present in it and is close to the high quality image. The sharpness of the image is retained unlike in the case of linear filtering. In the case where an image is corrupted with Gaussian noise, the wavelet shrinkage denoising has proved to be nearly optimal. Proposed method produces the best SNR compared to BayesShrink. However, the output from BayesShrink method is much closer to the high quality image and there is no blurring in the output image unlike the other two methods. It has been observed that BayesShrink is not effective for noise variance higher than 0.05. Denoising salt and pepper noise using Proposed method has proved to be efficient due to adaptive median filter used in it. When the noise characteristics of the image are unknown, denoising by multifractal analysis has proved to be the best method. It does a good job in denoising images that are highly irregular and are corrupted with noise that has a complex nature. In the two methods considered, namely multifractal regularization and multifractal pumping, the second method produces visually high quality images.

Since selection of the right denoising procedure plays a major role, it is important to experiment and compare the methods. As future research, we would like to work further on the comparison of the denoising techniques. If the features of the denoised signal are fed into a neural network pattern recognizer, then the rate of successful classification should determine the ultimate measure by which to compare various denoising procedures . Besides, the complexity of the algorithms can be measured according to the CPU computing time flops. This can produce a time complexity standard for each algorithm. These two points would be considered as an extension to the present work done.

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