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Efficient Image Denoising using DWT Reverse Bi-Orthogonal Filter

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Abstract - The image denoising techniquesare in the current trend of research to enhance the quality of digital graphics processors with automatic image denoising function in digital cameras. The denoising algorithms work towards the reduction of effect of noises by finding the irregularity in the pixel intensities distribution. The irregularity can be found and removed with the help of filters. These filters are of various fundamental structures like wavelet filters, Median filter, Weiner filter etc. In this paper we are utilizing the Reverse Bi-Orthogonal Filter of DWT for grayscale image denoising. From the comparison with the previous methodologies used it is found that the proposed denoising methodology having better results than existing work.

Keywords - Denoising, DWT, Reverse Bi-Orthogonal Filters, PSNR, RMSE and Gaussian Noise.

I. INTRODUCTION

Image denoising is often used in the field of photography or publishing where animage was somehow degraded but needs to be improved before it can be printed. For thistype of application we need to know something about the degradation process in order todevelop a model for it. When we have a model for the degradation process, the inverseprocess can be applied to the image to restore it back to the original form. This type ofimage restoration is often used in space exploration to help eliminate artifacts generatedby mechanical jitter in a spacecraft or to compensate for distortion in the optical systemof a telescope. Image denoising finds applications in fields such as astronomy where theresolution limitations are severe, in medical imaging where the physical requirements forhigh quality imaging are needed for analyzing images of unique events, and in forensicscience where potentially useful photographic evidence is sometimes of extremely badquality.

Let us now consider the representation of a digital image. A 2-dimensional digitalimage can be represented as a 2-dimensional array of data s(x,y), where (x,y) representthe pixel location. The pixel value corresponds to the brightness of the image at location(x,y). Some of the most frequently used image types are binary, gray-scale and colorimages.

Binary images are the simplest type of images and can take only two discretevalues, black and white. Black is represented with the value ‘0’ while white with ‘1’.Note that a binary image is generally created from a gray-scale image. A binary imagefinds applications in computer vision areas where the general shape or outlineinformation of the image is needed. They are also referred to as 1 bit/pixel images.Gray-scale images are known as monochrome or one-color images. The imagesused for experimentation purposes in this paper are all gray-scale images. They containno color information. They represent the brightness of the image. This image contains 8bits/pixel data, which means it can have up to 256 (0-255) different brightness levels. A‘0’ represents black and ‘255’ denotes white. In between values from 1 to 254 representthe different gray levels. As they contain the intensity information, they are also referredto as intensity images.

Color images are considered as three band monochrome images, where each bandis of a different color. Each band provides the brightness information of thecorresponding spectral band. Typical color images are red, green and blue images and arealso referred to as RGB images. This is a 24 bits/pixel image.

Principles of DWT

Wavelets are the mathematical functions which analyze data according to the scale or resolution. They help in studying a signal in different windows or in different resolutions. For example, if the signal is viewed in the large window, gross feature can be noticed, and if viewed in a small window, only the small features can be noticed. The wavelets provide some advantages over Fourier transforms. For instance, they do a great job in approximating signals with sharp spikes and signals having discontinuities. Wavelets can also model music, speech, video and non-stationary stochastic signals. The wavelets can be used in applications such as turbulence, image compression, human vision, earthquake prediction, etc.

The term “wavelets” is referred to a set of orthonormal basis functions generated by translation and dilation of scaling function φand a mother wavelet ψ. A finite scale multi resolution representation of a discrete function is called as a discrete wavelet transform. DWT is a fast linear operation on the data vector, whose length is an integeral power of 2. This transform is orthogonal and invertible where the inverse transform expressed as the matrix is the transpose of the transform matrix. The wavelet base or function, different sines and cosines in Fourier transform, is localized in space. Similar to sines and cosines the individual wavelet functions are localized in frequency.

The orthonormal base or wavelet basis can be defined as

$$\psi_{(j,k)}(x) = 2^{j/2}\psi(2^j x - k)$$

The scaling function is given as

$$\phi_{(j,k)}(x) = 2^{j/2}\phi(2^j x - k)$$

Where ψ is the wavelet function and j and k are integers that scale and dilate the wavelet function. Factor ‘j’ in Equations is called as the scale index, which indicates the width of the wavelet. The location index k provides the position. The wavelet function is dilated from the powers of two and is translated by the integer k. In terms of the wavelet coefficients and the wavelet equation is given:

$$\psi(x) = \sum_{k}^{N-1} g_k \sqrt{2\phi(2x-k)}$$

Where g0, g1, g2…. are high pass wavelet coefficients. The scaling equation in terms of scaling coefficients as given below

$$\phi(x) = \sum_{k}^{N-1} h_k \sqrt{2\phi(2x-k)}$$

The function φ(x) is the scaling function and the coefficients h0, h1,…..are low pass scaling coefficients. The wavelet and scaling coefficients are related by the quadrature mirror relationship, that is

$$g_n = (-1)^n h_{1-n+N}$$

Whereas N is the number of vanishing moments.

Properties of DWT

Wavelets are a mathematical tool which can be used to extract information from many kinds of data, including audio signal and the images. Mathematically, the wavelet ψ, is a function of zero average and having the energy concentrated in time:

$$\int_{-\infty}^{\infty} \psi\ (t)\, dt\ =\ 0$$

In order to be more flexible in extracting time and frequency informations, a family of wavelets can be constructed from a function ψ (t), also known as the ‘Mother Wavelet’ that is confined in a finite interval. ‘Daughter Wavelets’, $\psi_{u,s}(t)$ are then formed by translation with a factor u and dilation with a scale parameter s:

$$\psi_{u,s}\ (t)\ =\ \frac{1}{\sqrt{s}} \cdot \psi\left(\frac{t-u}{S}\right)$$

Wavelet Analysis

The wavelet analysis is performed by projecting the signal to be analyzed on the wavelet function. It implies a multiplication and integration:

$$x\ (t), \psi_{u,s}\ (t)\ =\ \int x\ (t)\psi_{u,s}\ \ (t)\ dt.$$

Depending on the signal characteristics that we want to analyze, we can use different scales and translations of the mother wavelet. The wavelet analysis is that it allows us to change freely the size of the analysis function (window), to make it suitable for the needed resolution, in time or frequency domains. For the high resolution in time-domain analysis we want to ‘capture’ all the sudden changes that appear in the signal, and we do that by using a contracted version of the mother wavelet. Conversely, for high-resolution in the frequency-domain we will be using a dilated version of the same function.

- DWT is a fast linear operation that can be applied on data vectors having length as integral power of 2.
- DWT is invertible and orthogonal. The scaling function φ and the wavelet function ψ are orthogonal to each other, i.e., $<\varphi, \psi> = 0$.
- The wavelet basis is localized in the space and frequency.

The coefficients satisfies some constraints

$$\sum_{i=0}^{2N-1} h_i = \sqrt{2}$$

$$\sum_{i=0}^{2N-1} h_i h_{i+2l} = \delta_{1,0}$$

Here δis the delta function and l is the location index.

$$\sum_{i=0}^{2N-1} (-1)^i i^k h_i = 0$$

Additive and Multiplicative Noises

Noise is undesired information that degrades the image. In the image de-noising process, information of the type of noise present in the original image plays a significant role. Mostly images can be corrupted with noise modeled with either a uniform, Gaussian, or salt and pepper distribution.

Another type of noise is a speckle noise which is multiplicative in nature. Noise is present in image either in an additive or multiplicative form.

Rule for additive noise

$$w(x, y) = s(x, y) + n(x, y) \;, \ldots\ldots\ldots\ldots\ldots(1)$$

Rule for multiplicative noise

$$w(x, y) = s(x, y) \times n(x, y) \;, \ldots\ldots\ldots\ldots\ldots(2)$$

where (x,y) is original signal, n(x,y) is the noise introduced into the signal to produce a noisy image w(x,y), and (x,y) is the pixel location. The above image algebra has been done at pixel level. Image addition also has applications in image morphing. Image multiplication means the brightness of the image is varied.

The digital image acquisition process transforms an optical image into a continuous electrical signal that is, sampled. In every step of the process there are fluctuations caused by natural phenomena, adding random value to the exact brightness value for a given pixel.

Additive white Gaussian noise (AWGN)

The standard model of amplifier noise is additive, Gaussian, independent at each pixel and independent of the signal intensity, caused primarily by Johnson–Nyquist noise (thermal noise). In color cameras where more amplification is used in the blue color channel than in the green or redchannel, there can be more noise in the blue channel[14]. Gaussian noise is a noise that has its PDF equal to that ofthe normal distribution, which is also known as the Gaussian distribution. Gaussian noise is most commonly known as additive white Gaussian noise. Gaussian noise is properly defined as the noise with a Gaussian amplitude distribution [15]. Among various image-denoising strategies, the transform-domain approaches in general, and in particular the multiscale ones, are very efficient for AWGN reduction[16].

Wavelet functions

In choosing the wavelet function, there are several factors which should be considered

1. Orthogonal or Non-orthogonal - In orthogonal wavelet analysis, the number of convolutions at each scale is proportional to the width of the wavelet basis at that scale. This produces a wavelet spectrum that contains discrete "blocks" of wavelet power and is useful for signal processing as it gives the most compact representation of the signal. Unfortunately for time series analysis, a periodic shift in the time series produces a different wavelet spectrum. Conversely, a nonorthogonal analysis (such as used in this study) is highly redundant at large scales, where the wavelet spectrum at adjacent times is highly correlated. The nonorthogonal transform is useful for time series analysis, where smooth, continuous variations in wavelet amplitude are expected.

2. Complex or real. A complex wavelet function will return information about both amplitude and phase and is better adapted for capturing oscillatory behavior. A real wavelet function returns only a single component and can be used to isolate peaks or discontinuities.

3. Width. For concreteness, the width of a wavelet function is defined here as the e-folding time of the wavelet amplitude. The resolution of a wavelet function is

determined by the balance between the width in real space and the width in Fourier space. A narrow (in time) function will have good time resolution but poor frequency resolution, while a broad function will have poor time resolution, yet good frequency resolution.

4. Shape. The wavelet function should reflect the type of features present in the time series.For time series with sharp jumps or steps, one would choose a boxcar-like function such as the Haar, while for smoothly varying time series one would choose a smooth function such as a damped cosine. If one is primarily interested in wavelet power spectra,then the choice of wavelet function is not critical, and one function will give the same qualitative results as another.

II. WAVELET DECOMPOSITION AND THRESHOLDING

Wavelet is a mathematical function used to divide a given function or continuous-timesignal into different scale components. One can assign a frequency range to each scalecomponent. Each scale component can then be studied with a resolution that matches itsscale. Thus the Wavelet is a multi resolution representation function.Wavelet transform is the discrete sampling of the wavelets. Based on the recurrencerelations property of wavelet, the most common wavelet transforms, such as Daubechieswavelet transform, generate progressively finer discrete samplings of an implicit motherwavelet function; each resolution is twice that of the previous scale down-sampled by 2.Therefore, using the one level wavelet transform, the input signal can be decomposedinto two frequency coefficients, the approximation coefficients as the low frequency partand the detail coefficients as the high frequency part. This is the so called waveletdecomposition.

With higher level decompositions, multi resolution representation of the signal can beachieved. Fig.2.1 shows the wavelet decomposition of an image. The left picture is theoriginal image and the right one using 1-level wavelet decomposition. We can see from theright image that the top left small picture is the low frequency part which keeps the energy mostly while the others are detail information.

Wavelet thresholding is a denoising method that applies the thresholding shrinkage upon the high frequency components after the wavelet decomposition. There are two basic thresholding methods, the hard thresholding and the soft thresholding, by which the threshold value is computed.

Fig.2.1Wavelet decomposition of the left picture. It uses Db4 of1 level wavelet decomposition.

Discrete Wavelet Transform

The non linear methods for denoising have gained the attention of the researchers these days. These methods are mainly based on thresholding the Discrete Wavelet Transform (DWT) coefficients, which have been affected by additive white Gaussian noise[17]. The DWT is basically the decomposition of the signal that provide better spatial and spectral localization. When a signal is decomposed, it is known as analysis, that in mathematical manipulation means discrete wavelet transform. When this decomposed signal is reconstructed, it is known as synthesis that mathematically means inverse discrete wavelet transform. Basically the denoising algorithms that use wavelet transform: calculating the wavelet transform of the noisy signal, modifying the noisy wavelet coefficients and computing the inverse transform using the modified coefficients. In the process of decomposition of an image by DWT, the transform coefficients are modeled as independent identically distributed random variables with generalized gaussian distribution (GGD).

Wavelet Thresholding

It has been noticed that in many images energy is mostly concentrated in a small number of dimensions with their coefficients relatively large compared to otherdimensions or to any other images (specially, noise) that has its energy spread over a large number of coefficients.Hence, in wavelet thresholding, method each coefficient is thresholded (set to zero) by comparing against a threshold to remove noise, while retaining important image coefficients. Usually two types of thresholding techniques are used soft and hard.

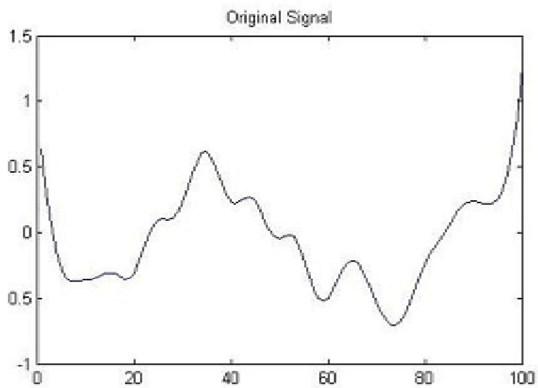
1. Hard Thresholding - Hard thresholding is a keep or kill procedure. This method produces artifacts in the images as a result of removing large coefficients. Hard thresholding does not even work with some algorithms

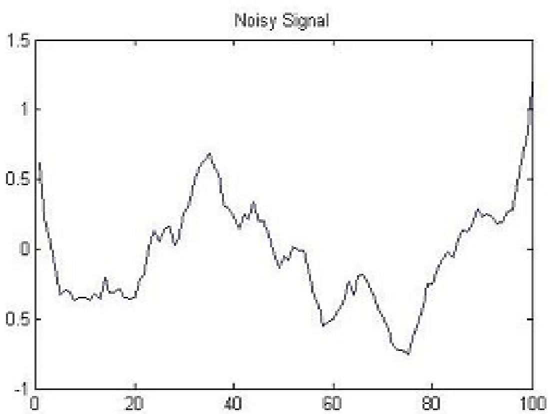
like sure shrink to overcome the demerits of hard thresholding, the wavelet transform with soft thresholding was introduced.

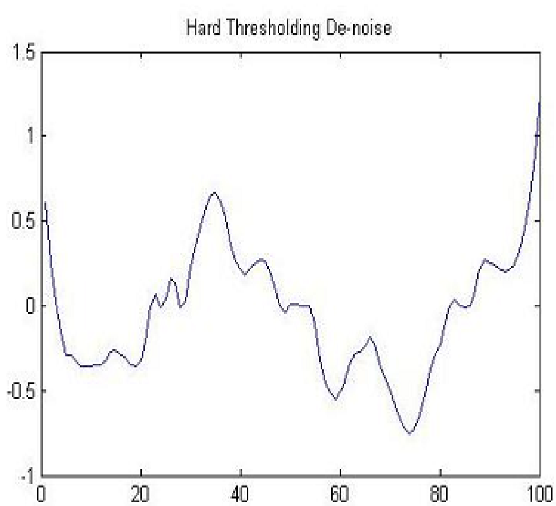
The hard thresholding operator is defined as

$$D(V, \lambda) = V \text{ for all } |V| > \lambda \quad (3)$$

$$= 0 \text{ otherwise.}$$







Example of Hard Thresholding

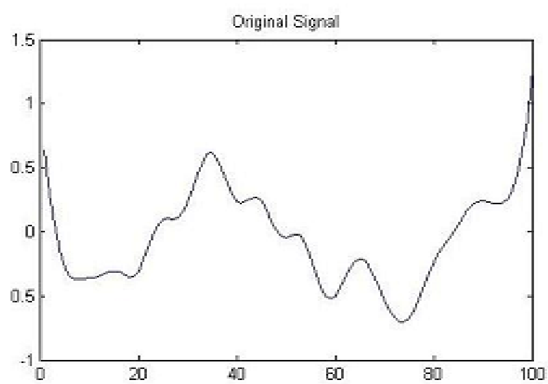
2. Soft Thresholding - Soft thresholding preserves the edges by smoothening them. Soft thresholding results in reducing the coefficients above the threshold in absolute value. The soft thresholding shrinks the coefficients above the threshold in absolute value. It is a shrink or Dekill rule[18].

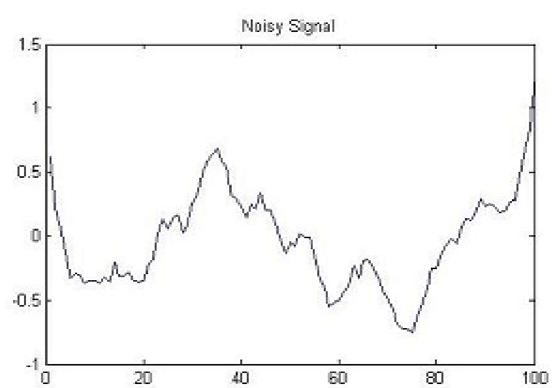
   The soft thresholding operator is defined as

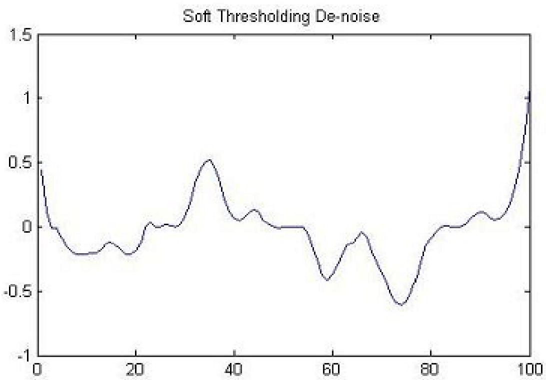
$$D(V, \lambda) = 0 \text{ for all } |V| \leq \lambda \quad (4)$$

$$= \text{sgn}(V)(|V| - \lambda) \text{ otherwise}$$

Choosing the threshold value is crucial as larger valuemay result into loss of image information while smaller one may allow noise to continue. The thresholding techniques also have disadvantages. In case of hard thresholding, they may not continuous atthe threshold which may lead to the oscillation of the reconstructed image. In the soft thresholding case, thereare deviations between image coefficients and thresholded coefficients which directly influence the accuracy of the reconstructed image.







Example of Soft Thresholding

Another problem with this is retention of edge. Different edge detectionalgorithms are used to extract the contour feature of cell images. To overcome the edge retention problem the best opted method is bilateral filtering.

Wiener Filter

Denoising Techniques

Various denoising techniques have been proposed so far and their application depends upon the type of image and noise present in the image. Image denoising is classified intwo categories:

1. Spatial domain filtering - This is the traditional way to remove the noise from the digital images to employ the spatial filters. Spatial domain filtering is further classified into linear filters and non-linear filters [19].

1.1 Linear Filters - A mean filter is the optimal linear for Gaussian noise in the sense of mean square error. Linear filters tend to blur sharp edges, destroy lines and other fine details of image. It includes Mean filter and Wiener filter [19].

a. Mean Filter- This filter acts on an image by smoothing it. It reduces the intensity variations between the adjacent pixels. Mean filter [20] is nothing just a simple sliding window spatial filter that replaces the centre value of the window with the average values of its all neighboring pixels values including itself. It is implemented with the convolution mask, which provides the results that is weighted sum of vales of a pixel and its neighbors. It is also called linear filter. The mask or kernel is square. Often 3×3 mask is used. If the coefficient of the mask sum is up to one, then the average brightness of the image is not changed. If the coefficient sum to zero, average brightness is lost, and it returns a dark image.

b. Weiner Filter - Weiner filtering [21] method requires the information about the spectra of noise and original signal and it works well only if the underlying signal is smooth. Weiner method implements the spatial smoothing and its model complexity control corresponds to the choosing the window size.

The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach.The purpose of the Wiener filter is to filter out the noise that has corrupted a signal. This filter is based on a statistical approach. Mostly all the filters are designed for a desired frequency response. Wiener filter deal with the filtering of an image from a different view. The goal of wienerfilter is reduced the mean square error as much as possible. This filter is capable of reducing the noise and degrading function. One method that we assume we have knowledge of the spectral property of the noise and original signal. Weused the Linear Time Invariant filter which gives output similar as to the original signal as much possible [22].

It uses the following Function

J = wiener2(I, [m n], noise)[23]

Filters the image I using pixelwise adaptive Weiner filtering, using neighborhoods of size m-by-n to estimate the local image mean and standard deviation. If you omit the[m n] argument, m and n default to 3. The additive noise (Gaussian white noise) power is assumed to be noise.

1.2 Non- Linear - With the non-linear filter, noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on the group of pixels with the assumption that noise occupies the higher region of frequency spectrum. Generally spatial filters remove the noise to reasonable extent but at the cost of blurring the images which in turn makes the edges in the picture invisible.

a. Median Filter –Median filter [20] follows the moving window principle and uses 3×3, 5×5 or 7×7 window. The median of window is calculated and the center pixel value of the window is replaced with that value.

2. Transform domain filtering - The transform domain filtering can be subdivided into data adaptive and non-adaptive filters. Transform domain mainly includes wavelet based filtering techniques [19].

Types of Noise

Various types of noise have their own characteristics and are inherent in images in different ways.

1. Amplifier Noise (Gaussian Noise) - The standard model of amplifier noise is additive, Gaussian, which is independent at each pixel and independent of the signal intensity. In color cameras, blue colour channels are more amplified than red or green channel, therefore, blue channel generates more noise [24].

2. Impulsive Noise - Impulsive noise is also called as salt-and- pepper noise or spike noise. This kind of noise is usually seen on images. It consists of white and black pixels. An image containing salt and pepper noise consists of two regions i.e. bright and dark regions. Bright regions consist of dark pixels whereas dark regions consist of bright pixels. Transmitted bit errors, analog-to-digital converter errors and dead pixels contain this type of noise [25].

3. Speckle Noise- Speckle noise is a multiplicative noise. It is a granular noise that commonly exists in and the active radar and synthetic aperture radar (SAR) images. Speckle noise increases the mean grey level of a local area. It is causing difficulties for image analysis in SAR images .It is mainly due to coherent processing of backscattered signals from multiple distributed targets [24].

III. PROPOSED DENOISING APPROACH

In this work we have utilizes the wavelet filter which is Reverse Bi-Orthogonal filter with level 3 by applying level independent hard thresholding. For little more enhancement above system is followed by Weiner filtering. The block diagram of the proposed denoising technique is given in the Fig. 3.1.

The above blocks are implemented using image processing functions of simulation tool. The computer algorithm and its step by step flow is shown in the Fig. 3.2. The algorithm starts with the taking and grayscale image as input which is original without any noise.

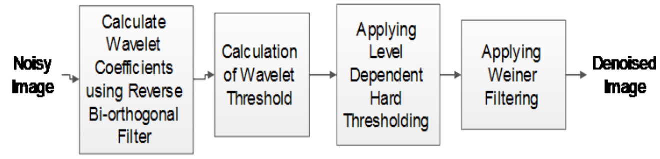


Fig. 3.1 Block Diagram of the Proposed Denoising Model

The some gaussian noise of 0.05 density is added into the image. Now the main part of the algorithm starts with the calculation of wavelet coefficients using reverse bi-orthogonal filter followed by calculation of wavelet threshold. Now based on the coefficients calculated and threshold will be applied on the Noisy image with level independent thresholding

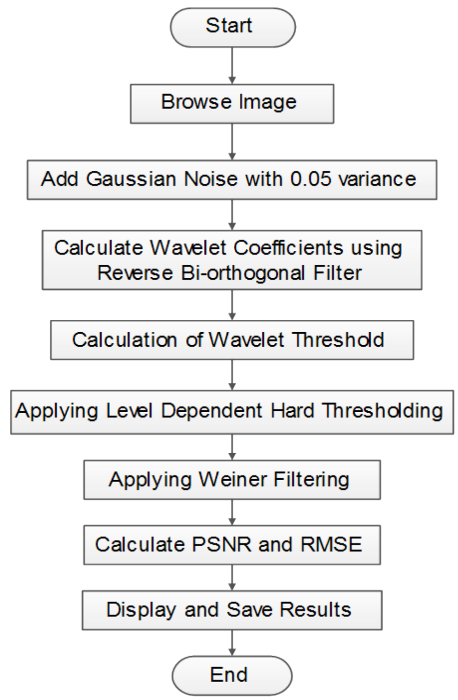
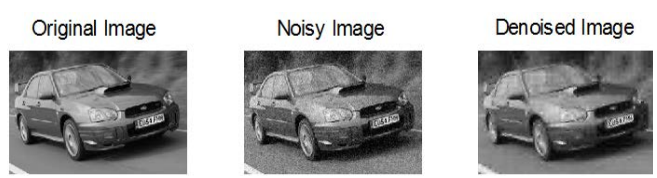


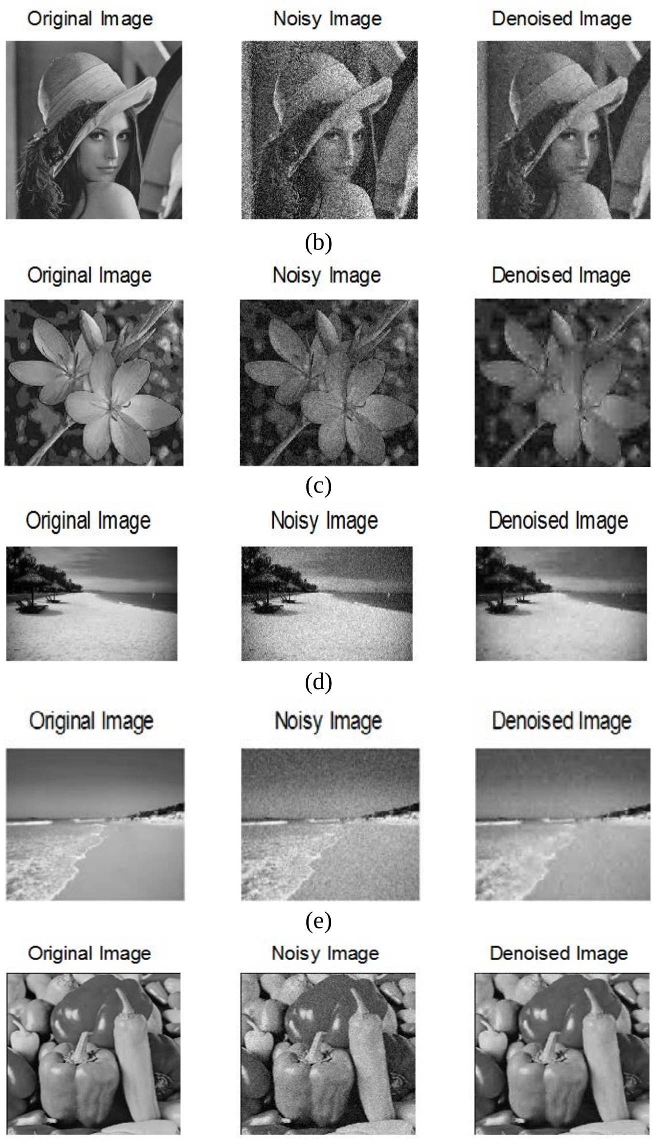
Fig. 3.1 Flow chart of the Proposed Denoising Algorithm

IV. SIMULATION RESULTS

The simulation of the proposed denoising algorithm is explained in the previous section. In this section the outcomes of the proposed methodology at various stage is shown below with the numerical comparison with the existing work. The results of the denoised images are shown in the Fig. 4.1 below.



(a)



(f)

Fig. 4.1 Original Image, Noisy Image and Denoised Image of (a) Car, (b) Lena, (c) Red Flower, (d) Beach, (e) Beach2 and (f) Pepper

Images we have taken as per the existing research so that we can compare our proposed methodology for better outcomes. Table I shows the Root Mean Square Error (RMSE) and Peak Signal to Noise Ratio (PSNR) for six different grayscale images with existing work. Table II shows the comparison of Peak Signal to Noise Ratio (PSNR) for different Gaussian Noise Densities of Noisy Image, Existing Work and Proposed Methodology.

TABLE - I COMPARISON OF PERFORMANCE OF THE EXISTING WORK AND PROPOSED WORK IN TERMS OF PSNR AND RMSE FOR VARIOUS IMAGES

Images	**Existing Work**		**Proposed Methodology**	
	RMSE	**PSNR**	**RMSE**	**PSNR**
Car	17.11	23.46 dB	14.9	**24.7 dB**
Lena	15.48	24.33 dB	8.9	**29.2 dB**
RedFlower	13.13	25.76 dB	13.1	**25.8 dB**
Beach	12.94	25.88 dB	10.3	**27.9 dB**
Beach2	12.98	25.86 dB	9.1	**28.9 dB**
Peppers	19.44	22.35 dB	9.9	**28.3 dB**

TABLE - II COMPARISON OF PERFORMANCE OF THE EXISTING WORK AND PROPOSED WORK IN TERMS OF PSNR AND RMSE WITH DIFFERENT GAUSSIAN VARIANCE

Noise Variance	**PSNR in dB**		
	Noisy Image	**Existing Work**	**Proposed Methodology**
0.05	13.84	23.46	**29.20**
0.1	11.51	21.23	**27.90**
0.15	10.35	19.81	**26.80**
0.2	9.60	18.92	**26.00**
0.25	9.12	18.30	**25.20**
0.3	8.70	17.74	**24.70**
0.35	8.39	17.24	**24.30**
0.4	8.18	17.01	**23.80**

The PSNR achieved in this paper with proposed methodology achieved is 25% improvement with 29.2dB from 23.46 dB.

V. CONCLUSION AND FUTURE WORK

The image denoising approach shown in this paper is proved efficient for various images and also for various noise densities of Gaussian Noise. The Effectiveness of the proposed approach is compared with the existing work in terms of Peak Signal to Noise Ratio (PSNR) and Root Mean Square Error (RMSE). The average percentage improvement from previous work is about 25% and such performance is appreciable. The wavelet filters utilized in proposed algorithms can be more efficient with other filters like Daubechies, Symlet, Haar and Bi-Orthogonal filters with different thresholding and filter levels.

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