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An Improved Image Denoising Technique Using Multi-Level Decomposition and Wiener Filter

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ABSTRACT

With the advent of digital technology, digital images have gained unprecedented importance. Digital images are subject to various transformations and blurring effects during capturing, transmission through a channel, reception, retrieval and storage. These unwanted signals bringing about unwanted changes and degradations in the image are referred to as noise. Different types of noise have different statistical and stochastic properties. The effect of noise can be profound resulting from partial to complete loss of information contained in the signals. Therefore the effect of noise needs to be nullified to the possible extent. The process of removing noise from images is termed as image denoising. The main challenge pertaining to image denoising is the detection of various types of noise in an image and subsequently designing a filter that would alleviate the effect of noise without affecting the original image as much as possible.

In this paper, we proposed a method in which multi-level decomposition of images is carried out and then using a Wiener filter to mitigate the affect of various types of noise. To analyze the performance of proposed work, Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are calculated. The main aim is to obtain a high value of PSNR and a low value of MSE and compared with previously existing techniques. It has been observed that the proposed method achieves better results as compared to previously existing techniques.

Keywords: - Image Denoising, Wavelet Transform, Wiener Filter, Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Gaussian Noise, Salt & Pepper Noise, Speckle Noise, Poisson Noise.

1. INTRODUCTION

An image may be defined as a two dimensional function, I= *f(x, y)* where x and y are spatial co-ordinates i.e. co-ordinates corresponding to space or location. The function I essentially contains two basic pieces of information, one being the intensity at a point also called the gray scale value and the R-G-B value which tells about the colour or frequency aspect of the image. If it happens so that the values of (x, y), and the gray level [*f(x, y)*] are finite and discrete values, then such an image is called a digital image.

If we process the digital images using a digital computer, then this process is called digital image processing. Digital images comprise of finite number of elements each of which has a finite location and value. These elements are called picture elements, image elements, or pixels. Digital images have immense applications ranging from education, defense and military, banking, electronic vision, photography to video filming, medical etc. But during the capturing, storage and retrieval, transmission and receiving of images, they are affected by various types of noise. This process degrades the quality of the images and the degradation can be nominal to severe depending upon the degradation phenomena [2].

Noise is a random signal and the degradation of images by noise is a random process [5]. Therefore we need to help the probabilistic techniques to analyze the degradation phenomena. Image denoising refers to the process of removing the effects of noise that have affected the image of interest. For inverting the effect of degradation on images, we need to have the knowledge of the probabilistic parameters that are used to analyze different types of noise such as mean, variance, standard deviation etc.

Degradation can corrupt or change either the intensity value or the R-G-B value or both corresponding to a pixel values. The degradation can be attributed to blurring from diffraction and noise from a variety of sources.

Image Denoising is a fundamental problem in computer vision application and image processing that has been researched since the earliest day of digital images [2] .For denoising of image, variety of the linear and non linear methods have been developed. Many methods are specially focused on noise reduction and others attempt to handle the multiple degradations jointly such as blur and noise. A most commonly used method for image restoration, relevant to this paper, is Wiener filter [3].The standard wiener filter is linear space-invariant filter acting upon to the image degradation assuming quasi stationary random process and noise. It should be kept in mind though that the wiener filter can be customized to be applied to different noise effects.

In the proposed work, we design a model for degradation of images by different types of noise. Then an inverting model for Image Denoising is designed. The most critical decision to take regarding image denoising is the choice of a proper image filter. It is desirable to have a filter which is ultra wide band in nature that is to say which has a filtering frequency response well beyond the entire spectrum that different images can occupy. But practically, it’s not possible to design such a filter which shows such ultra wideband behavior. Therefore we breakdown the images into different frequency sub bands and apply the filtering operation in the sub bands to remove the effects of noise from the entire spectrum which the image occupies. This breaking down of signals into different sub bands is achieved using the tool called Wavelet Transform.

For least harmonic distortions, it is desirable that the filter is linear and space invariant in nature. Therefore in the proposed work we have chosen the Wiener filter which is linear and space invariant in nature. Images are subjected to the combined effects of blurring and addition of various types of noise, affecting images commonly to degrade the images. Then the wavelet transform is applied on the degraded images and finally they are filtered using the Wiener filter to get back the denoised image. It is desired that the denoised image and the original image be as close as possible. For the analysis of proposed methods, two performance parameters are taken, Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

In the concluding part of the work, PSNR and MSE values are calculated and compared with previously existing techniques and validated for a set of images comprising of different images.

2. LITERATURE REVIEW

Khaled M Mohamed et al. clarify a new patch-based image restoration algorithm using an adaptive Wiener filter (AWF) with a novel spatial-domain multi-patch correlation model. The new filter structure is referred to as a collaborative adaptive Wiener filter (CAWF). The CAWF employs a finite size moving window. At each position, the current observation window represents the reference patch. We identify the most similar patches in the image within a given search window about the reference patch. A single-stage weighted sum of all of the pixels in the similar patches is used to estimate the centre pixel in the reference patch [10].

V Gupta, R Mahle, and R.S. Shriwas, presented in their research paper, denoising of images using several thresholding methods such as Sure Shrink, Visu Shrink and Bayes Shrink. They gave results of different approaches of wavelet based image denoising methods and extended the existing technique and providing a comprehensive evaluation of the proposed method. The results based on a range of noise, such noise as Gaussian, Poisson's, Salt and Pepper, and Speckle have been achieved in this work. SNR and MSE are as a measure of the quality of denoising was preferred. Wavelet algorithms are very helpful tool for signal processing such as image compression and image denoising [11].

Boyat, A; Joshi, B.K., explored a new image denoising algorithm based on combined effect of wavelet transform and median filtering. The method removes the noise from the image and improves the quality. The level of wavelet decomposition is limited to three. The well-known index Peak Signal to Noise Ratio and Root Mean Square Error demonstrate marked improvement of image denoising greater than other methods [12].

Mariana S. C. Almeida et al. has suggested that a Non-blind method is the one in which the point spread function or blurring operator is known and in blind method, the point spread function is assumed to be unknown [13].

Ruikar, S.; Doye, D.D., Presented a new approach of threshold function developed for image denoising algorithms. This uses wavelet transform in connection with the threshold functions for removing noise. General, Bayes Shrink, Visu Shrink, normal shrink and Sure Shrink are compared with our threshold function, the SNR efficiently improved by this [14].

Deepa Kundur et al suggested that the restoration process uses cost function which consists of three components. The first penalizes the negative pixels of the image estimate inside the region of support. The second term penalizes the pixels of image estimate outside the region of support that are not equal to background color. The third component is used to constrain FIR filter coefficient away from trivial all zero global minimum. The advantage of this algorithm is that it entails the minimization of a convex cost function. Noise amplification at low signal to noise ratio is drawback of this method [15].

S. Derin Babacan et al., proposed to use variation methods for the blind deconvolution problem by incorporating a total variation function as the image prior and simultaneous autoregressive model as the blur prior. They have presented novel algorithms for total variation based blind deconvolution and parameter estimation utilizing a variational framework. Using a hierarchical baysian model, the unknown image, blurs and hyper parameters for the image, blur and noise priors are estimated simultaneously. This method gives high quality image restoration in synthetic and real image experiments [16].

Dong-Huan Jiang et al. demonstrated a new variational model for image restoration by incorporating a nonlocal TV regularize and a nonlocal Laplacian regularize on the image. The two regularizing terms make use of nonlocal comparisons between pairs of patches in the image. The new model can be seen as a nonlocal version of the CEP-*L*2 model. Subsequently, an algorithm combining the alternating directional minimization and the split Bregman iteration is presented to solve the new model. Numerical results verified that the proposed method has better performance for image restoration than CEP-*L*2 model, especially for low noised images [17].

3. VARIOUS SORCES OF NOISE

Noise is introduced in the image at the time of image acquisition or transmission. Different factors may be responsible for introduction of noise in the image. The number of pixels corrupted in the image will decide the quantification of the noise [4]. The principal sources of noise in the digital image are:-

(a). The imaging sensor may be affected by environmental conditions during image acquisition.

(b). Insufficient Light levels and sensor temperature may introduce the noise in the image.

(c). Interference in the transmission channel may also corrupt the image.

(d). If dust particles are present on the scanner screen, they can also introduce noise in the image.

4. TYPES OF NOISE

Digital images are prone to a variety of types of noise. Noise is the undesirable effects produced in the image [1]. During image acquisition or transmission, several factors are responsible for introducing noise in the image. Noise may be modeled by either the Histogram or probability density function. Noise is superimposed on original images.

Depending on the type of disturbance, the noise can affect the image to different extent. Generally our focus is to remove certain kind of noise. So we identify certain kind of noise and apply different algorithms to remove the noise.

Image noise can be classified as follows:-

- Gaussian Noise (Amplifier Noise)
- Poisson Noise (Shot Noise)
- Salt & pepper Noise (Impulse Noise)
- Speckle Noise(Multiplicative Noise)

4.1 Gaussian Noise (Amplifier Noise)

It is also called as electronic noise or amplifier noise because it arises in amplifiers or detectors. This noise model is additive in nature [4] and follow Gaussian distribution. Meaning that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value. The noise is independent of intensity of pixel value at each point. Gaussian noise generally disturbs the gray values in digital images.

Gaussian noise caused by natural sources such as thermal vibration of atom, discrete nature of radiation of warm objects and conversion of the optical signal into an electrical one. Gaussian noise can be reduced using a spatial filter.

4.2 Salt & pepper Noise (Impulse Noise)

Salt and pepper noise is sometimes called impulse noise or spike noise or random noise or independent noise or data drop-out noise. Black and white dots appear in the image [5] as a result of this noise and hence salt and pepper noise.

In Salt and pepper noise model has only two possible values, *a* and *b*. The probability of each is typically less than 0.1(otherwise, the noise would vastly dominate the image). The corrupted pixels are set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Unaffected pixels remain unchanged. For an 8-bit/pixel image, the typical value for pepper noise is close 0 and for salt noise is close to 255 [2].

An image containing salt-and-pepper noise will have dark pixels in bright regions and bright pixels in dark regions [4]. This type of noise can be caused by dead pixels, analog-to digital converter errors and bit errors in data transmission, malfunctioning of pixel elements in the camera sensors, faulty memory locations, or timing errors in the digitization process.

4.3 Speckle Noise (Multiplicative Noise)

Speckle noise is a multiplicative noise [2] .This noise can be modeled by random value multiplications with pixel values of the image and can be expressed as:-

$$J = I + n*I$$

Where, J is the speckle noise distribution image, I is the input image and *n* is the uniform noise image by mean *o* and variance *v*.

While Gaussian noise can be modeled by random values added to an image, speckle noise can be modeled by random values multiplied by pixel values hence it is also called multiplicative noise. Speckle noise is a major problem in some radar applications. Speckle noise follows a gamma distribution.

4.4 Poisson Noise (Shot Noise)

Poisson or shot photon noise is the noise that can cause, when number of photons sensed by the sensor is not sufficient to provide detectable statistical information [4]. This noise has root mean square value proportional to square root intensity of the image. Different pixels are suffered by independent noise values. At practical grounds the photon noise and other sensor based noise corrupt the signal at different proportions [3]. Shot noise follows a Poisson distribution, which is usually not very different from Gaussian.

5. WAVELET TRANSFORM

The discrete wavelet transform (DWT) [6],[7] of an image generate its non-redundant representation [8] that provides better spatial and spectral localization of image formation, compared with other multi scale representations such as Laplacian pyramid etc Time and frequency localization is simultaneously provided by Wavelet transform. Wavelet methods represent signals much more efficiently than either the original domain or Fourier transforms [9].
Image is decomposed into four sub-bands and critically sampled by applying DWT as shown in Fig. 1(a). These sub bands are formed by separable applications of horizontal and vertical filters. Sub-bands with label LH1, HL1 and HH1 correspond to finest scale coefficient while sub-band LL1 represents coarse level coefficients [9]. The LL1 sub band is further decomposed and critically sampled to find out the next coarse level of wavelet coefficients as shown in Fig. 1(b). It results in two levels wavelet decomposition. After L decompositions, a total of D (L) = 3 * L + 1 sub bands are obtained.

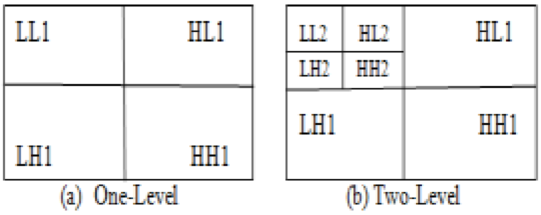


Figure1. Image Decomposition by using DWT

6. WIENER FILTER

The Wiener filter is a classic method for attempting to remove noise from images. It was developed by Norbert Wiener in the 1930's and 1940's.The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. The wiener filtering method requires the information about the spectra properties of the noise and the original signal and it works well only if the underlying signal is smooth [19]. Wiener filtering is able to achieve significant noise removal when the variance of noise is low; they cause blurring and smoothening of the sharp edges of the image [20].It removes the additive noise and inverts the blurring simultaneously. The Wiener filtering is optimal in terms of the mean square error [3]. Wiener filters are characterized by the following:-

(a). Assumption:- signal and (additive) noise are stationary linear random processes with known spectral characteristics.

(b). Requirement: - the filter must be physically realizable, i.e. causal (this requirement can be dropped, resulting in a non-causal solution).

(c). Performance criteria: - minimum mean-square error.

7. PROPOSED METHODOLOGY

The crux of the entire proposed methodology can be explained using the block diagram of proposed method. The block diagram of proposed method is explained under the following different heading.

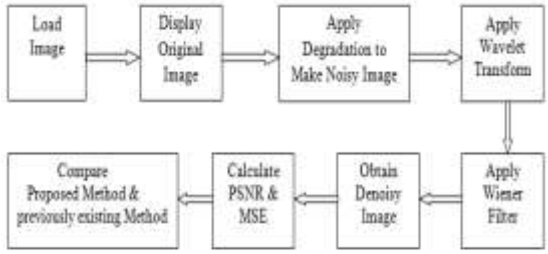
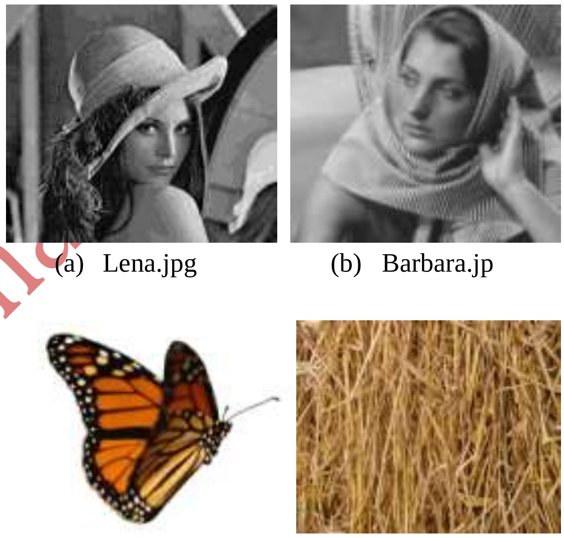


Figure2. Block Diagram of Proposed Method

7.1 Input Images

In this paper, we use standard test images for image processing applications. The format of images used here is .jpg. They are loaded into the MATLAB workspace and then analyzed.



(a) Lena.jpg (b) Barbara.jp

(c) Monarch.jpg (d) Straw.jpg

Figure3. Standard Test Image

7.2 Adding Blurring and Noise Functions

After the images are loaded into the MATLAB workspace, blurring and noise functions are added to the images and thus the obtain image are noisy blur image .The different types of noise added are Gaussian, Salt & Pepper, Speckle and Poisson. We show the noise and blur effects to Lena.jpg image. The same processes are applied to the other images.

7.3 Wavelet Analysis of Images

The main approach before applying filtering is wavelet analysis of the loaded image. The reason behind this is fairly simple. None of the filters

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available to us possess an ultra wideband frequency response. As the different types of noise occupy different frequency ranges, therefore it becomes important to first break the given signal into a fixed band and then apply the filtering process. The benefit of such an approach is the removal of noise from majority of the noise bands.

The breaking of the signal into a frequency bands is called decomposition of image signal. The tool used for this purpose is the Wavelet Transform. There are a variety of wavelet families such as Haar, Sym, and Coif etc depending on the base functions of the respective wavelets. Wavelets also allow us the provision of decomposing the given image into the number of frequency bands; we wish which is also called the level of decomposition. It should however be noted that an optimal level for decomposition should be chosen, ignoring which the complexity of the algorithm increases without exhibiting substantial improvements in the results. An illustration of wavelet decomposition of an image with family Haar and level 3 is illustrated below.

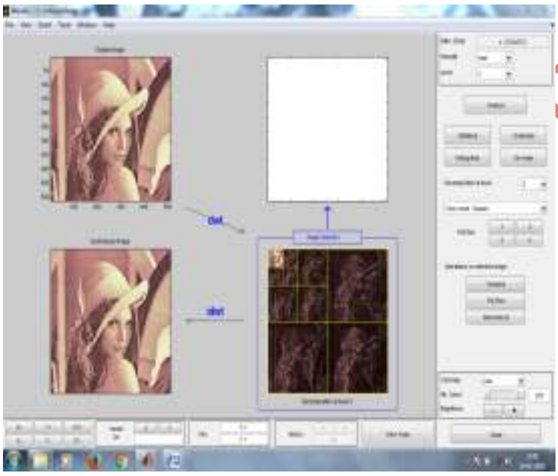

Figure4. Decomposition of Lena Image for Haar Family at Level 3 by using DWT

7.4 Image Denoising using Wiener filter

Image denoising refers to the process of removing the effects of noise from an image. There can be a variety of noises and blurring, which degrade the original signal. We need to take a most critical decision regarding image denoising is the choice of a proper image filter .The important characteristics that should be considered while choosing a particular filter are following:-

1) Linearity: - It ensures that higher order harmonic distortion does not occur and spurious frequency effects don't arise out of non linearity.

2) Space Invariance: - It ensures that shifting of pixels don't produce a detrimental effect on the filtering function.

The above requirements are fulfilled by the Wiener Filter which happens to be the fundamental reason behind choosing it for image denoising.

7.5 Performance evaluation using PSNR & MSE

The Peak Signal to Noise Ratio (PSNR) and mean square error (MSE) are the two important performance parameters which are used to measure the quality of image.

7.5.1 Mean Square Error (MSE)

The MSE represents the cumulative squared error between the encoded and the original image. The effectiveness of the algorithm stands in minimizing the mean square error. If F(X, Y) is the original image, G(X, Y) is the corrupted image and I(X, Y) is the denoised image then MSE is given by:-

$$MSE = \frac{1}{MN}\sum_{X=1}^{M}\sum_{Y=1}^{N}(F(X,Y)-I(X,Y))^2$$

A low of MSE indicates that the original and the denoised image are close in characteristics.

7.5.2 Peak Signal Noise Ratio (PSNR)

PSNR represents a measure of the ratio between maximum powers of signal to the power of noise. We are trying to increasing the value of PSNR to the extent possible. PSNR is inversely proportional to the MSE; its unit is in decibel (dB) and is formally defined by:-

$$PSNR = 10\log_{10}\frac{255^2}{MSE}dB$$

A high value of PSNR indicates that the effect of noise has been mitigated.

7.6 Comparison of Proposed method and Previously Existing method

In the final and last step of proposed methodology the comparison between proposed method and previously existing method are done in terms of performance evaluation parameter, PSNR and MSE values.

8. RESULTS AND DISCUSSION

In this study, the simulations have been carried out using MATLAB platform on set of standard test images. The basic operations are mentioned below.

8.1 Load Images

For the simulation work, standard test images are loaded into a MATLAB workspace and then analyzed.

8.2 Applying Blurring and Noise Function

Here, we need to design the blurring function using the convolution and apply to the image. We also need to specify stochastic noise parameters such as mean, variance, standard deviation etc of the different types of noise to be added to the image. Due to the effects of blurring and the various types of noise, the quality of image can be degraded. In this paper, the degradations can be categorized as follows:-

(1). Only Blurring.

(2). Blurring with Gaussian Noise.

(3). Blurring with Salt and Pepper Noise.

(4). Blurring with Speckle Noise.

(5). Blurring with Poisson Noise.

8.3 Image Decomposition using DWT

Image decomposition using wavelet transform comprise of the following steps:-

(1). Select wavelet family.

(2). Select level of decomposition.

(3). Show decomposed image.

(4). Display decomposition characteristics.

8.4 Applying Wiener Filter for Image Denoising

Here we need to call the filtering function for the Wiener filter through which the various type of noise and blurring effect to be removed. It should be noted that such a priori knowledge should be provided to the filter arguments prior to filtering.

This includes:-

(1). Assuming the Noise to Signal Ratio (NSR) of image = 0 and applying the filter.

(2). Estimating the Noise to Signal Ratio (NSR) of image and applying the filter.

8.5 Calculation of PSNR and MSE

The mean square error and PSNR give an indicative idea about the denoising capabilities of the proposed method. A comparative analysis of proposed method and previously existing method in term of, PSNR and MSE values leads to conclusive remarks about the effectiveness of the proposed methodology.

8.6 Results and Discussion:

Simulated results have been carried on standard test image by adding effects of blurring and four types of noise such as Gaussian noise, Salt&Pepper noise, Speckle noise and Poisson noise. Due to the effects of blurring and the various types of noise, the image becomes a noisy and degraded image. The Denoising of image is done using Wavelet Transform and Wiener Filter. Comparison is being made on basis of some performance evaluated parameters. These parameters are Peak Signal to noise Ratio (PSNR) and Mean Square Error (MSE).

Also the noisy and denoisy images of Lena considering the effects of blurring and different type of noise such as Gaussian noise, Salt & Pepper noise, speckle noise and Poisson noise are shown in Figure 10.

Table1 show the comparative study of PSNR and MSE value for different noise attack on Lena.jpg image.It can be seen that the maximum PSNR value and minimum MSE value for Poisson Noise and minimum PSNR value and maximum MSE for Gaussian Noise.

Table1. Comparative Study of PSNR and MSE Value for Different Noise Attack on Lena image

TYPE NOISE	PSNR	MSE
Gaussian Noise	**75.35**	**0.0019**
Salt& Pepper Noise	**78.84**	**0.00086**
Speckle Noise	**80.15**	**0.00063**
Poisson Noise	**83.52**	**0.00029**

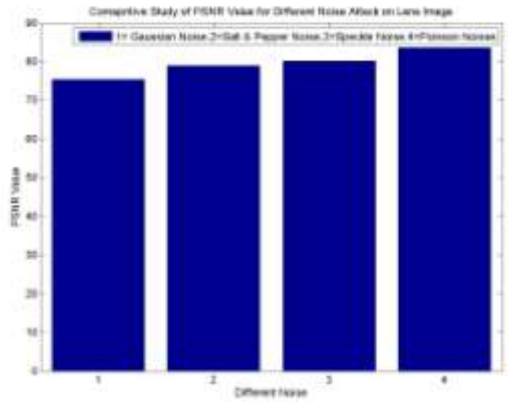

Figure5. Bar Graph of Comparative Study of PSNR Value for Different Noise Attack on Lena image

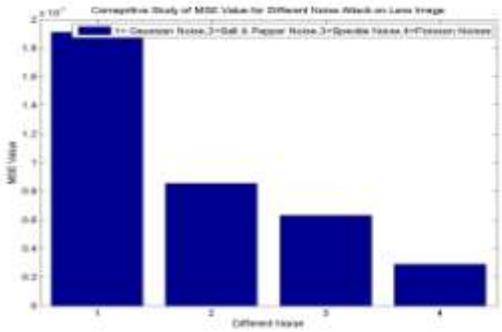

Figure6. Bar Graph of Comparative Study of MSE Value for Different Noise Attack on Lena image

Table 2 show the comparative study of PSNR value for different noise attack on different test images. It can be seen that the maximum PSNR value for Poisson noise on different test images.

Table 2.Comparative Study of PSNR Value for Different Noise Attack on Different Test Image

PEAK SIGNAL TO NOISE RATIO (PSNR)				
Name of Image	**Gaussian Noise**	**Salt & Pepper Noise**	**Speckle Noise**	**Poisson Noise**
Lena	**75.35**	**78.84**	**80.15**	**83.52**
Barbara	**75.23**	**71.11**	**77.59**	**80.11**
Monarch	**74.29**	**67.95**	**76.57**	**84.31**
Straw	**74.20**	**68.81**	**74.62**	**75.65**

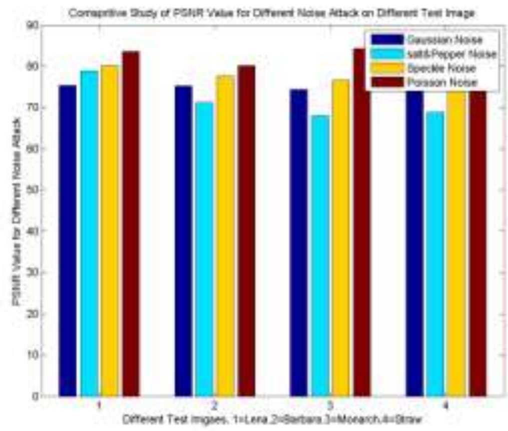

Figure7. Bar Graph of Comparative Study of PSNR Value for Different Noise Attack on Different Test Image

Table 3 show the comparative study of MSE value for different noise attack on different test images. It can be seen that the minimum MSE value for Poisson noise on different test images.

Table3.Comparative Study of MSE Value for Different Noise Attack on Different Test Image

MEAN SQUARE ERROR (MSE)				
Name of Image	**Gaussian Noise**	**Salt & Pepper Noise**	**Speckle Noise**	**Poisson Noise**
Lena	**0.0019**	**0.00086**	**0.00063**	**0.00029**
Barbara	**0.0020**	**0.0051**	**0.0011**	**0.00063**
Monarch	**0.0024**	**0.0105**	**0.0014**	**0.00024**
Straw	**0.0025**	**0.0086**	**0.0023**	**0.0018**

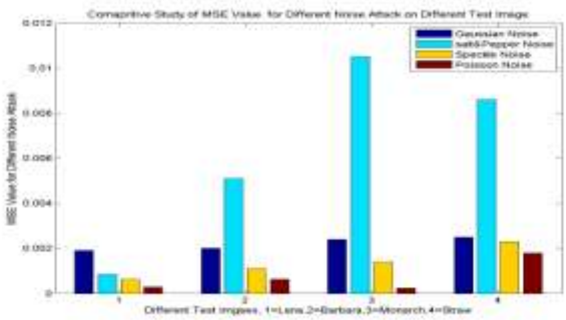

Figure8. Bar Graph of Comparative Study of MSE Value for Different Noise Attack on Different Test Image

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Table4 show the comparative study of proposed method and previously existing method* of PSNR valve for Gaussian noise with different test images. It can be clearly seen that the proposed method produces almost twice the value of PSNR for Gaussian noise on different test images as compared to the previously existing method. This can be done by using multi-level decomposition followed by filtering through Wiener filter. The effectiveness of proposed method has been evaluated with two standard parameters viz. Peak signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

*The previously existing method is taken from "Nonlocal Hierarchical Dictionary Learning Using Wavelets for Image Denoising (NHDW) by Ruomei Yan, Ling Shao and Yan Liu", IEEE Transactions, December 2013, which is considered as a base paper of my work.

Table4.Comparative Study of Proposed Method and Previously Existing Method of PSNR Valve for Gaussian Noise on Different Test Image

GAUSSIAN NOISE		
Name of Image	**Proposed Method**	**Previously Existing Method**
Lena	**75.35**	**35.89**
Barbara	**75.23**	**35.34**
Monarch	**74.29**	**34.48**
Straw	**74.20**	**31.70**

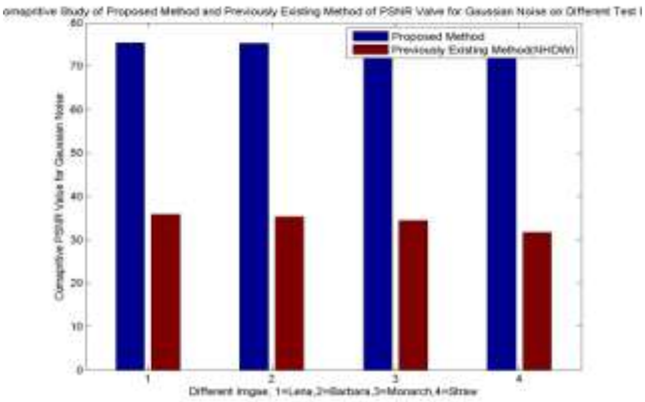

Figure9. Bar Graph of Comparative Study of Proposed Method and Previously Existing Method of PSNR Valve for Gaussian Noise on Different Test Image

It can be seen from the previous bar graphs that the value of PSNR increases with the decreasing values of MSE. It agrees with the common conceptions since with increasing similarity between the original image and denoised images, the mean square error tend to decrease. This results in the increasing value of PSNR. Also the comparative analysis between the proposed method and previously existing method has been done, it can be seen that the proposed technique achieves better results pertaining to PSNR and MSE.

(a) Original Image of Lena

(b) Blur Image

(c) Blur and Gaussian Noise Image

(d) Restoration of Blur and Gaussian Noise Image Using NSR=0

(e) Restoration of Blur and Gaussian Noise Image Using Estimated NSR

(f) Blur and Salt & Pepper Noise Image

(g) Restoration of Blur and Salt & Pepper Noise Image Using NSR=0

(h) Restoration of Blur and Salt & Pepper Noise Image Using Estimated NSR

(i) Blur and Speckle Noise Image

(j) Restoration of Blur and Speckle Noise Image Using NSR=0

(k) Restoration of Blur and Speckle Noise Image Using Estimated NSR

(l) Blur and Poisson Noise Image

(m) Restoration of Blur and Poisson Noise Image Using NSR=0

(n) Restoration of Blur and Poisson Noise Image Using Estimated NSR

Figure10. Show Noisy and Denoisy Image of Lena considering the effects of Blurring and Different Type of Noise such as Gaussian noise, Salt &Pepper noise, Speckle noise and Poisson noise from (a) to (n)

9. CONCLUSION

It can be concluded that the proposed technique achieves substantially better results than the previous technique. The high value of PSNR and low values of MSE can be attributed to the fact that in this technique. We use multilevel decomposition prior to filtering which helps in removing noise and blurring effects from multiple frequencies sub bands which the image may occupy. It can also be concluded that due to the linear nature of filtering used, non linear distortions are not introduced in the frequency band of interest and the pixel values are restored resulting in low MSE and high PSNR values.

It should be noted though that multi band decomposition tends to increase the computational and time complexity of the technique. Therefore the choice of proper level of decomposition and family of wavelet remains an optimization problem which renders a trade off between desired results and complexity. It is hoped though that with proper selection of wavelet family and level, the proposed technique will served to be a less complex yet powerful algorithm for image denoising.

10. FUTURE WORK

Future work can be considered to be improvement in the values of Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE), different techniques can be tried. The value of PSNR should be maximised and the value of MSE should be minimised, as much as possible. To achieve such results, one may use hybrid filtering techniques, where multiple filters can be used in conjugation. Although this may make the system computationally complicated, it is expected to yield better results.

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