ANALYSIS ON WAVELET BASED IMAGE COMPRESSION AND DENOISING FOR MEDICAL APPLICATION

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APPROVAL

This project titled **''Analysis on Wavelet Based Image Compression and De-noising for Medical Application''** submitted by D. K. Sheakh Sajib and Md. Monirul Islam to the department of Electronics and Telecommunication Engineering (ETE), Daffodil International University, has been accepted as satisfactory to the partial fulfilment of the requirements for the degree of B.Sc. in Electronics and Telecommunication and approved as to its style and contents. The presentation was held on November, 2019.

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We hereby declare that this project is our own work and effort under the supervision of **Prof. Dr. A. K. M. Fazlul Haque, Professor, Department of Electronics and Telecommunication Engineering,** Daffodil International University, Dhaka. It is not been submitted anywhere for any award. Where other sources of information have been used, they have been acknowledged.

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ABSTRACT

The medical images carry very sensitive data in order to detect the abnormalities in the organ of a body. These images contain huge information and the images size is too large to store the images, that's why it requires huge space causing an extra cost and the images are affected by different noises during transmission. The bandwidth management can grounds the extra cost, so compression can be the solution to overcome the drawbacks. The aims of the project is to compress the medical image in a popular existing method of Wavelet 2D analysis. The project is divided into 2 parts as the noisy image analysis and de-noised image analysis. The noises are added in the image and de-noised images are considered to analysis the actual susceptibility to the actual images. The noisy images and de-noised images are analyzed in the Wavelet 2D and different variations are observed by their statistical analysis. The compression ratio of different compression threshold methods are also compared in the result section and performance of different filter has also been observed.

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CHAPTER 1

INTRODUCTION

1.1 Overview

In clinical practice the medical imaging plays an inescapable role. The images are very sensitive especially Magnetic Resonance Imaging (MRI), Computed tomography (CT scan), Ultrasound, X-Ray etc. These images are very essential to diagnosis many complicated diseases. These medical images require high Bandwidth, high data whereas the channel bandwidth is not enough sufficient. So it is very important to take a look at how these images are transmitted perfectly. Because of limited bandwidth and storage capacity So Before storing these images and transmitting these images it is required to compress these images. But when the images are transmitted then the images are affected by some noises especially Salt & Pepper noise, Gaussian noise, Speckle noise Sinusoidal noise etc. Since these images are very sensitive that's why any kind of noises are not acceptable in medical image processing. So the image should be de-noise. Before doing this, considered some noises which are only applicable of ideal images and this noises are added. Then the images are compressed by Discrete Wavelet Transform in 2D and de-noise the images by using different filters in MATLAB programming. In this research work it is considered that only Median filter, Wiener filter, Linear filter and Gaussian filter to de-noise the affected image and these filters are successfully used in medical imaging. The MRI image is taken because this image is most affected by Salt & Pepper noise, Speckle noise, Gaussian noise and Sinusoidal noise. The different statistical comparison is found and observed in different compressed images, noisy images and the Histogram of different noisy, de-noised image.

1.2 Literature Review

The foundation of clinical images is around the start of the 20th century, after the invention of the x-ray. This started within radiology, however it took off at some stage in the second global conflict. The first step of medical imaging was with x-rays that would be exceeded via the frame onto a few film, which would generate a picture. They might take in to 11 mins, and would situation the affected person to 50 instances more radiation than an x-ray these days, which takes simply milli-seconds. After that it was once in the Nineteen Sixties that computer-based photo analysis com-menced to appear, which means that it has been round for almost 60 years. However, there have been many advances seeing that they have been first introduced, especially with the introduction of digitalization in the 1970s. Any kind of medical image is not easy to perceive since it carry a lot of data, information. Nowadays there are huge number of clinical images are stored, processed and transmitted but the channel bandwidth is limited as a result compression is needed to save the storage and transmission bandwidth. The wavelet Transform is defined by Yves Meyer and J. Lemarie offers good locations in both space and frequency domains, and fast algorithms can be implemented. Since the discrete wavelet transformation (DWT) was presented by Mallat, due to its well-time-frequency decomposition, many researchers on signal analysis and image compres-sion have developed fruitful results [1]. The wavelet transformation has been widely used in signal processing research over the past ten years, particularly in image compression. Wavelet-based schemes achieve better performance in many applications than other DCT-based coding schemes. Because the input picture does not need to be blocked and its basic elements have variable length coding schemes based on wavelets can avoid blocking artifacts. Wavelet-based coding also ena-bles incremental image transmission [2]. The DCT is a computational process that converts digital image data from the spatial domain into the frequency domain. Sonja Grgic explores a series of wavelet functions (wavelets) for implementation in the compression model of images and high-lights the benefit of this transformation in comparison to the methods of today. This measures the effects of various wavelet functions, image quality and compression ratios [3]. In the year 2012, the new image compression scheme was defined by M. Mozammel Hoque Chowdhury with a pruning proposal based on discrete wavelet transformation (DWT). Some actual pictures explained the efficacy of the algorithm, and the algorithm's representation was compared with other common compression standards. Their empirical results show that the proposed technique offers appropriate high compression ratios compared to other compression techniques [4]. Now Noise reduction techniques have become an important method for the study of anatomical structure and image processing of visual images from MRI in medical imaging appeal. In the year, 2017 Hanafy M. Ali investigated the representation of three different completely filtering methods (Median filter (MF), Adaptive Median filter (AMF) and Adaptive Wiener filter (AWF)) tested with different noises on Magnetic Resonance Imaging (MRI) images in MRI Medical Image De noising by Fundamental Filters chapter in his book [5]. The filter choice depends on the type and quantity of noise in the image.

1.3 Motivation of the Project

As the importance of diagnostic pictures in the clinical profession is enhanced for various appeal including; care planning to identify the disease and disorders in various human body organs. Any type of degradation of the quality and fact incompatibility is a great threat to diagnosis in medical application. That's why the implication of image processing is also enhanced. And wavelet transform is the best way to analysis an image because wavelet transform can track out the small change of abnormalities in an image. Hence image compression is lossless and lossy. Compressed data can be used to reconstruct an exact replica of the original in a lossless compression method; no information is lost to the compression process and this compression is known as entropy coding. Though in lossless compression the compression ratio is not high. But in lossy the initial signal can't be correctly extracted from the compressed data when compressed and the compression ratio is better. In this project it has been tried to get some variation in different thresholding method when compressed in the existing method in a Haar wavelet.

1.5 About the report

This is an organized report which contains 6 chapters. The first chapter provides the total overview of the project. The image analysis based on wavelet is discussed in chapter 2. The chapter 3 is methodology where different methods of analysis were discussed about the original brain MRI image and noisy image. Chapter 4 is described about the analysis of de noising used different filter. In chapter 5 the result and analysis are described based on chapter 3 and 4. Finally chapter 6 includes the total outcome of this project.

CHAPTER 2

WAVELET BASED IMAGE ANALYSIS

To understand the specifications of compression and de noising of the medical image, we have to know the features of Wavelet Transform. Section 2.1 depicts about the basic Wavelet Transform.

2.1 Introduction:

A wavelet is a wave-like oscillation with an amplitude beginning at zero, increasing, and then dropping back to zero. Usually, it can be perceived as a "short oscillation" like a seismograph or heart monitor registered. Wavelets are generally designed purposely to have unique properties that make them useful for signal processing. Wavelets can be paired with known portions of a damaged signal to extract information from unknown portions using a "reverse, shift, divide and integrate" technique called convolution [6]. Wavelet transform is able to together providing data on time and frequency, thereby giving the signal a time-frequency delegation. The basic idea of the transformation of the wavelet is to represent an arbitrary function like such a linear combination of a set of such wavelets or basic functions. These basic functions are obtained via dilations (scaling) and translations (shifts) from a single prototype wavelet called the mother wavelet [2]. Therefore, sets of complementary wavelets are useful in compression or decompression algorithms based on wavelets where it is desirable to recover with minimal loss the relevant information. Basically, A wavelet function Ψ(t) has two main proper functions,

$$\int_{-\infty}^{0} \Psi(t)dt = 0; \qquad (1)$$

That is, the function is swinging or appears wavy.

$$\int_{-\infty}^{0} |\Psi(t)|^2 dt < \infty; \qquad (2)$$

That is, the most of the energy is limited to a finite duration in Ψ(t) [4].

2.2 Fourier and Wavelet Transform

The Fourier transform moves a sample of data or information to the frequency domain from the time domain. This enables to break into its main frequencies an apparently random set. It is used in all sorts of processing of signals. As known, the Fourier Transform is commonly used for signal and image processing and interpretation. It basically transforms time based signals to frequency based signals.

Figure 2.2: Fourier Transform [7]

Fourier Transform shows that as a sum of sine wave functions, each waveform can be re-written. The mathematical expression of Fourier transform is defined as,

$$f(\omega) = \int_{-\infty}^{\infty} f(t).e^{-i\omega t}dt \qquad (3)$$

Where, $\omega = 2\pi f$ and $|f(\omega)|$ = Amplitude of each component ω of the signal.

There is also the reverse Fourier transform, which is used with the reconstruction of the original function to transform the signal from a frequency domain to a time domain. Equation (4) describes mathematically the inverse Fourier transform,

$$f(t) = \int_{-\infty}^{\infty} f(\omega).e^{-i\omega t}d\omega \qquad (4)$$

Fast Fourier Transform (FFT) is an effective implementation of the Discrete Fourier Transform that can be applied to the signal when the samples are spaced evenly. FFT decreases the complexity of the computation by using the DFT's self-like properties. If the input is a non-periodic signal, the signal is not accurately represented by the overlay of the periodic basic functions. One way to overcome this problem is to expand the signal and make it intermittent at both ends. Windowed Fourier Transform (WFT) is another approach. The window method locates the signal in time by positioning the accent in the center of the window and attenuating the signal at both ends to zero [8]. Wavelet transforms allow a signal to be decomposed so that frequency characteristics and the position of specific characteristics in a time series can be simultaneously highlighted. Basically, the simple Wavelet Transform is almost similar to the well-known Fourier Transform. Like the Fourier Transform, the coefficients are determined by an input signal inner product with a set of orthonormal standard functions (this is a small subset of all wavelet transforms available). There is a difference that is, the Wavelet transform is a multi-resolution transform, that is, it enables a form of time-frequency analysis when using the Fourier Transform, the effect is a very detailed analysis of the frequencies found in the signal, but no data on when those frequencies occurred [8]. Discrete Wavelet Transforms are such kind of wavelet transform for which the wavelets are sampled discretely. Haar wavelets, Daubechies wavelets and the dual-tree complex wavelet transform (DCWT) are basic examples of DWT. The Discrete Wavelet Transform of a signal x is determined by passing it through a series of filters. Then at first the samples are passed through a low pass filter with impulse response and resulting in a convolution of the two.

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k] \qquad (5)$$

The signal is also decomposed at the same time by using a high-pass filter h. The outputs give the coefficients of information (from the high pass filter) and the coefficients of approximation (from the low pass filter). It is essential that the two filters are interrelated with one another and are known as a mirror filter for quadrature [8].

2.3 Different Wavelet Families

The program for $Wavelet\ Toolbox^{TM}$ contains a large number of wavelets which can be used for both continuous and discrete analysis. The Morlet, Meyer, derivative of Gaussian, and Paul wavelets are used to describe for continuous analysis in the wavelet toolbox software and for discrete analysis, the Haar wavelets, Daubechies wavelets, Symlets, Biorthogonal wavelets are used in the wavelet toolbox software. Wavelet choice is determined by the characteristics of the signal or picture and the complexity of the application. One can choose a wavelet that is tailored for application when understand the properties of the analysis and synthesis wavelet.

Short name of Wavelet Family	Wavelet Family Name
'haar'	Haar wavelet
'db'	Daubechies wavelets
'sym'	Symlets
'coif'	Coiflets
'bior'	Biorthogonal wavelets
'rbio'	Reverse biorthogonal wavelets
'meyr'	Meyer wavelet
'dmey'	Discrete approximation of Meyer wavelet
'gaus'	Gaussian wavelets
'mexh'	Mexican hat wavelet (also known as the Ricker wavelet)
'morl'	Morlet wavelet
'cgau'	Complex Gaussian wavelets
'shan'	Shannon wavelets
'fbsp'	Frequency B-Spline wavelets
'cmor'	Complex Morlet wavelets
'fk'	Fejer-Korovkin wavelets

Figure 2.3: Wavelet Family

2.3.1 Haar Wavelet

Haar wavelet is a series of rescaled "square-shaped" functions that together form a group or base of wavelets. It is compactly supported, the oldest and simplest method. In a scaling function $\varphi(t)$, 'Haar' is described as in the equation (6),

$$\varphi(t) = \begin{cases} 1 & 0 \leq t \leq 1, \\ 0 & otherwise. \end{cases} \qquad (6)$$

On the other hand, In a wavelet function the 'haar' can be described by the equation (7)

$$\psi(t) = \begin{cases} 1 & 0 \leq t < 0.5 \\ -1 & 0.5 \leq t < 1 \\ 0 & otherwise \end{cases} \qquad (7)$$

Basically Haar represents the same as db1 [9]. The Haar sequence is recognized as the first known wavelet base and widely used as an example of teaching nowadays. Alfred Haar invented the Haar series in 1909 [10]. Haar is orthogonal, biorthogonal and also compact supported. , this property may be an advantage in analyzing signals with abrupt transitions, such as tracking machine tool failure [11].

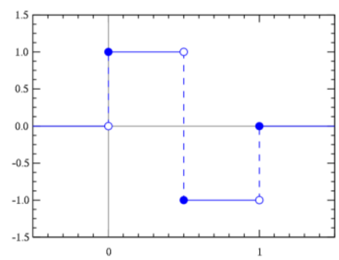


Figure 2.3.1: Haar Wavelet [12]

In this project work only the Haar wavelet family is examined. Haar is orthogonal, compactly supported and also symmetric. On the other hand Daubechies, Coiflets, Biorthogonal wavelet families has a major drawbacks which is their asymmetry, it may cause artifacts at wavelet subbands boundaries.

2.4 Reason to choose MRI image

MRI can be used to visualize some types of abnormalities or disorders that are not seen by CT, X-Ray and even fluoroscopic radiography. It has had far-reaching applications in the area of medical sciences since its discovery in the mid-80s. MRI is basically an anti-invasive technique that generates accurate anatomical images without disastrous radiation, as is the case for X-Ray radiography. MRI enables separate visualization of the body's soft-tissues and non-osseous components without ionizing x-rays harming. Magnetic Imaging Resonance can distinguish between white matter and gray matter in the brain and can also be used to track out aneurysms and tumors. There are many sources by which the MRI image can be affected into noise. We think the primary sources of noise in MRI image can be:

1. The interferences in the electronics receiver system.
2. Radiofrequency emissions in the patient body receiver due to the thermal ions movement.
3. The MRI scanner's measuring string i.e. tubes, electronic circuits etc.

Noise in MRI induces random fluctuations due to signal-dependent data bias, which decreases image contrast. It disturbs both the precise qualitative and quantitative analysis and the objects identification of MR images.

2.5 Principle of Image compression based on DWT

The compression of images is one of the important factors for storing or transmitting images over any communication media. Compression allows accessible, storable and communicable dimensions to be created in file sizes. Compression allows accessible, storable and communicable dimensions to be created in file sizes. Two distinct structural elements are composed of the image compression system. These are an encoder and a decoder. Image $f(x, y)$ is fed into the encoder which generates a set of input data symbols and uses them to illustrate the image. Image $\hat{f}(x, y)$ refers to an approximation of the image input resulting from the compression and subsequent decompression of the image input.

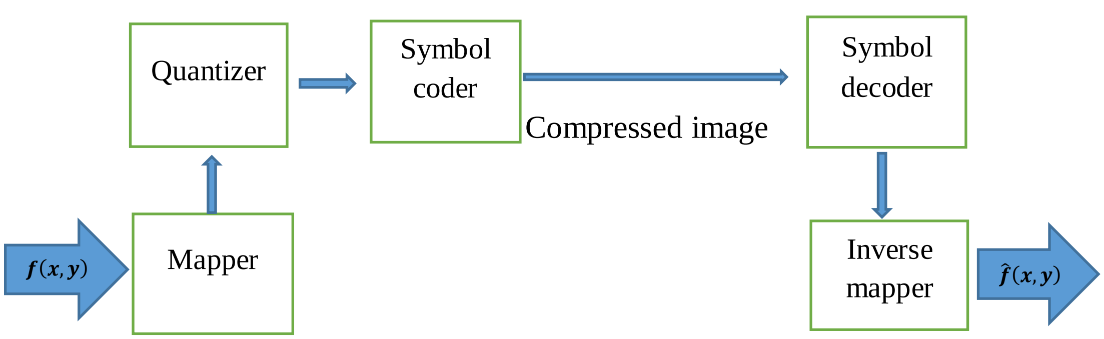


Figure 2.5(a): Basic structure of an image compression [4]

Two basic compression components are redundancy and reduction of irrelevancy. Redundancy reduction is intended to remove duplication from the image source of the signal [13]. The image is taken in HL, LH, HH, LL ratios in the Discrete Wavelet Transform. After that the image will be moved to DWT transforms, and DWT Quantization will be processed then. The system is then transferred to the DPCM encoder. Then we get the data from the compressed image and the compression ratio of the output image is also well. In a wavelet based compression the basic structure of compression is given below.

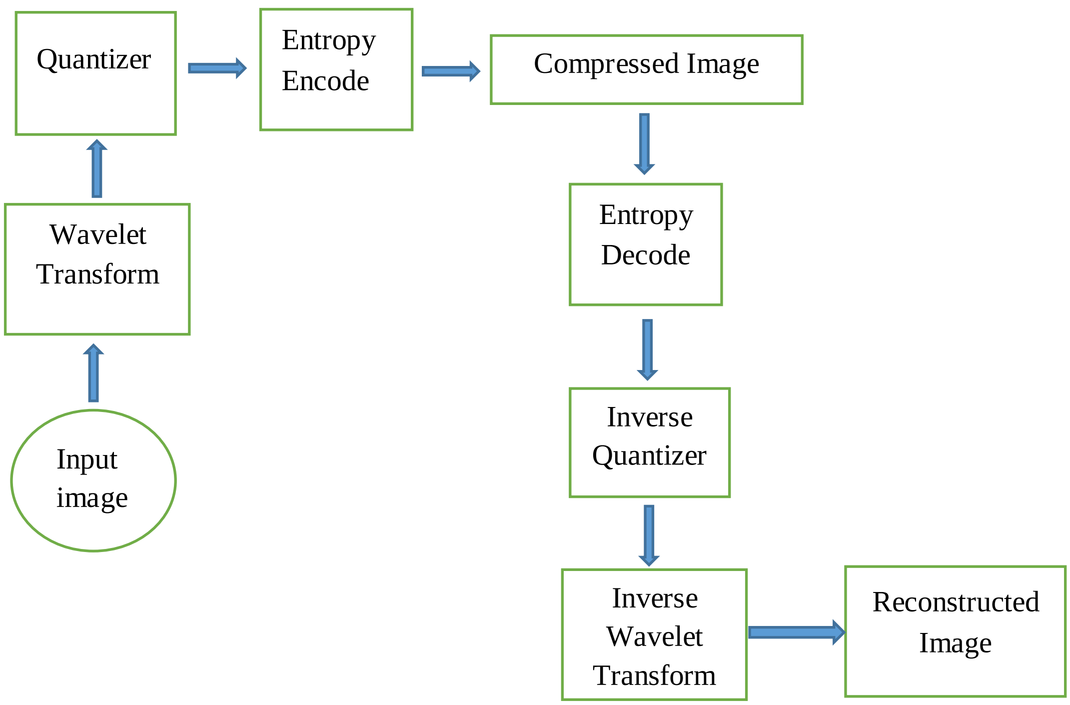


Figure 2.5(b): Basic structure of wavelet based image compression [4]

2.6. Image Compression Techniques

As we have told before image compression is a form of digital image data compression which is used to reduce the cost of stored system and also transmission. Algorithms can take advantage of visual perception and the image information with statistical properties to achieve superior results compared to standard methods of data compression used for other digital data. There are many approaches to compression of images, but they can be classified into two specific groups:

- lossless compression or reversible compression and
- Lossy compression or nonreversible compression

2.6.1 Lossless Compression

In a lossless image compression techniques, after compression the reconstructed image is numerically same to the original image on the basis of pixel by pixel without any data or information loss. Since in this technique no information is compromised and that's why it is desirable. Lossless compression is used in situations where the original and the decompressed data are the same, or where differences from the original data are unfavorable. Many image file formats, such as PNG and GIF which use only lossless compression but TIFF or MNG, can use both lossless and lossy methods. Most lossless compression programs do two things in a sequence: the first step generates a statistical model for input data, and the second step uses this model to map input data to bit sequences so that "probable" (e.g. frequently found) data produces shorter output than "improbable" data.

Algorithm for lossless compression:

- RLE(Run Length Encoding)
- Huffman Encoding
- Arithmetic Encoding
- Predictive Coding
- Chain Codes
- Area coding

2.6.2 Lossy Compression

In a lossy image compression techniques, after compression the reconstructed image contains degradations relative to the original image on the basis of pixel by pixel with some loss of information. For this the compression ratio is higher than lossless compression. Most of the lossy compression algorithms contain three stages: Transformation, Quantization and Encoding. Transformation is the process where the image is transformed from grayscale to coefficients, Quantization is the process where data integrity loss occurs and Encoding is the process where reduced coefficients are presented in a compact format. In many situations, the reconstruction of the main image is not necessary or even desirable. If there is some noise, the error due to that noise will typically be significantly reduced by some form of de noising method. In this case, it may be permissible that the small amount of error which is caused by lossy compression. Lossy compression is also acceptable when still images are fast transmitted over the Internet. Many image file format such as JPEG and GUI image file format use lossy compression. Lossy can't be used in all types of file since it deals with data removal. The information is not redundant because the text and data can't be compressed [14].

Algorithm for lossy compression:

- Transform coding
- Discrete Cosine Transform
- Discrete Wavelet Transform

CHAPTER 3

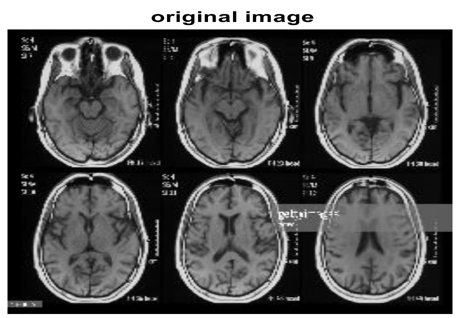
Methodology

3.1 2D wavelet analysis of Original Brain MRI image And Brain MRI Noisy image

To understand the analysis of compressed image and noisy image, it is first necessary to understand the properties the original image which is taken. Section 3.1describes about the property of the original image.

3.1.1 Properties of Original Brain MRI image

Properties of original brain MRI image in grayscale:



Width	: 430 pixels
Height	: 349 pixels
Horizontal Resolution	: 96 dpi
Vertical Resolution	: 96 dpi
Bit Depth	: 24

Figure 3.1.1(a): Brain MRI original image in grayscale

A gray-scale image is one in which the quality of each pixel is a single sample reflecting only the amount of light, i.e. only it carries brightness data or information. Grayscale images is a kind of monochrome black-and-white or brown which is consist exclusively shades of gray. The taken image is converted to grayscale. Figure 3.1 shows the brain MRI original image in grayscale. A pixel is basically nothing more than a dot. It is also known as picture element. The pixels are combined to form a complete image. Each pixel has a unique logical address, a size of 8 bits or more, and the ability to manipulate millions of different colors in most high-end display devices. In the figure below the image contains Width-450 pixels and Height 349 pixels. So that the total pixels of the image is (450 × 349) 157050. If each pixels contains 3 bits then this picture contains total 471150 bytes. The 96 dpi in Horizontal Resolution describes that 96 dots can be placed in a line within the span of 1 inch (2.54 cm) in horizontal axis and also vertical axis. Bit depth refers to the image's color data. The higher a picture's bit size, the more colors it can hold. So in this image bit depth 24 means the image may display over sixteen million colors.

3.2 Statistical analysis and compression of Original brain MRI image

At first the original image is saved in '.mat' format from the workspace in MATLAB. After that the '.mat' file is loaded by “Wavelet Toolbox” for analysis in ‘2D wavelet’ window. In 2D analysis the image is decomposed at level 2 into four bands. These bands are LL (left-top), HL (right-top), LH (left-bottom) and HH (right-bottom).The HL band indicates the x axis variation and the LH band indicates the y axis variation gradually. After the thresholding process, the image is reconstructed using inverse wavelet transform. For further analysis we have taken the statistical parameters and screenshot of “histogram” and “cumulative histogram” for Brain MRI original image in different modes. Synthesized image is a new image with some kind of image description.

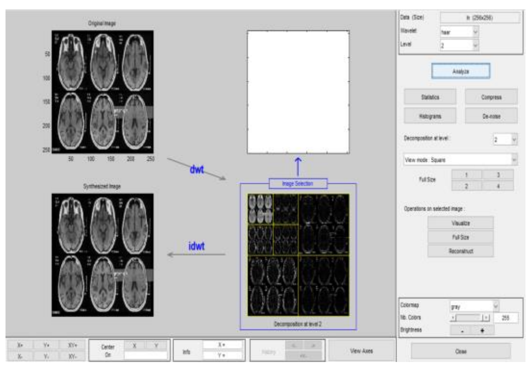


Figure 3.2(a): Original image decomposition at level 2

Mean	69.8	Maximum	255	Standard dev.	65.25	L1 norm	4.575e+06
Median	63	Minimum	0	Median Abs. Dev.	54	L2 norm	2.446e+04
Mean	7.65	Range	255	Mean Abs. Dev.	56.17	Max norm	255

Mean	69.8	Maximum	255	Standard dev.	65.25	L1 norm	4.575e+06
Median	63	Minimum	0	Median Abs. Dev.	54	L2 norm	2.446e+04
Mean	1.821	Range	255	Mean Abs. Dev.	56.17	Max norm	255

Mean	69.8	Maximum	247.5	Standard dev.	60.37	L1 norm	4.575e+06
Median	71	Minimum	0	Median Abs. Dev.	58.5	L2 norm	2.363e+04
Mean	7.425	Range	247.5	Mean Abs. Dev.	52.57	Max norm	247.5

Mean	0	Maximum	106.3	Standard dev.	12.71	L1 norm	3.681e+05
Median	0	Minimum	-106.3	Median Abs. Dev.	1.25	L2 norm	3255
Mean	2.125	Range	212.5	Mean Abs. Dev.	5.617	Max norm	106.3

Figure 3.2(b): Statistical values of original Brain MRI image

3.2.1 Different Statistical Parameter

To understand the analysis of statistical measurements it is necessary to discuss about different statistical parameter. Although in our thesis we have focused on only the value of standard deviation in different image to measure and different compressed image but another statistical parameter is also discussed briefly.

- **Mean:** The mean of an image refers about the arithmetic average of a set of pixel values in an image. It may be achieved by combining up all pixel and partition by the total number of pixels. It indicates the average value of a signal. It can be defines as

$$\bar{x} = \frac{\sum_{i=1}^{k} x_i}{N} \qquad (8)$$

Where, $\bar{x} =$ the mean,

$\sum_{i=1}^{k} x_i =$ the sum of all the scores in the set

$N =$ the number of scores in the set

In an image the mean value gives the contribution of separate pixel strength for the total image. Filtering using mean is labeled as temporal filtering in the contest of image processing and is used for noise reduction.

- **Median:** Median is a pixel strength level metric that distinguishes the value pixels of high strength from the value pixels of lower strength. The median is a usually used metric of the statistics and possibility theory elements of a data set. The median's fundamental benefit in put forward data as compared to the mean (often just characterized as the "normal") is that it is not so distorted by a small ratio of exceptionally large or small values, thereby giving a better understanding of a "typical" value.
- **Maximum:** For a grayscale images, the pixel value is a single number that represents the brightness of the pixel. The most common pixel format is the byte image, where this number is stored as an 8-bit integer giving a range of possible values from 0 to 255. Typically zero is taken to be black, and 255 is taken to be white, and there is maximum value of pixel.
- **Minimum:** zero is taken to black and 255 is white, and 0 is the minimum value of pixel.

- **Range:** The range is the difference between the maximum and minimum value.
- **Standard Deviation:** Standard Image Deviation is known as the variance's square root. Variance is nothing but the magnitude difference around the image's mean strength value. If the size of the variance is similar to the mean, there is less standard deviation. It is a measure of variance or diversity that is most frequently used in statistics. This indicates how much variance or "dispersion" from the standard (mean or predicted value) occurs in terms of image processing [15].

  The standard deviation of sample is defined as

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \qquad (9)$$

- **Median Absolute Deviation:** It is a metric of statistical dispersion. In regards, the median absolute deviation is a vigorous metric that is more active than the standard deviation for outliers in a data set. The ranges from the mean are measured in the standard deviation, and broad deviations are weighted more heavily, so it can be heavily influenced by outliers.
- **Mean Absolute Deviation:** The mean absolute deviation is the measure of the absolute variance of the data around the average: the mean (absolute) deviation from the mean. A data set's MAD is the average distance from each data value to the mean.
- **L1, L2 and Max. Norm:** Norm is an amount that characterizes the object's length, size, or extent in some sense. Norms exist for complex numbers. It is the addition of the absolute pixel value in an image. It is also known as least absolute deviations (LAD), least absolute errors (LAE).L1 norm minimize the addition of absolute differences between the target value and estimated value. L2 norm is the addition of squared pixel values which is square root. It minimize the addition of the square of the differences between the target value and the estimated value. Max norm is the maximum of the absolute values of its components.

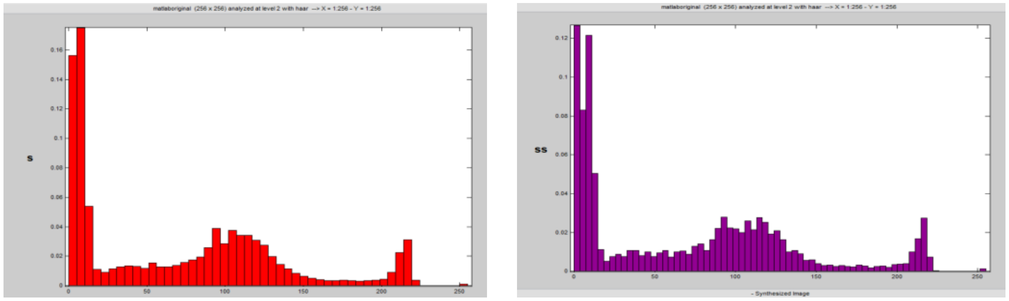


Figure 3.2(c): Histogram of Original Brain MRI image (bins 50) and Synthesize image (bins 70)

These histograms represents a graphical presentation of data that uses bars of various heights. That bar category is numbered into ranges in a histogram. For brain MRI original image the range is 0 to 255 as we known by statistical table and for synthesized image the value changes because we have increased the number of bins in 70 and the variance figure appear as shown above. So Larger bars indicate that more data is falling within that range. A histogram shows the continuous sample data features and breadth.

Table 3.2.2: Statistical analysis of the original Brain MRI image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Recon-structed In Approxima-tions	Recon-structed In Detail	Balance spar-sity-norm	Remove near-zero	Bal. spar-sity-norm
Mean	69.8	69.8	69.8	0	69.8	69.8	69.8
Median	63	63	71	0	71.44	63	63
Mean	7.65	1.821	7.425	2.125	8.698	6.316	8.144
Maximum	255	255	247.5	106.3	273	255	257.9
Minimum	0	0	0	-106.3	-70.25	-1.375	-5
Range	255	255	247.5	212.5	343.3	256.4	262.9
Standard dev.	65.25	65.25	60.37	12.71	59.89	65.25	65.17
Med. Abs. dev.	54	54	58.5	1.25	54.72	54.06	54.19

M. Abs. dev.	56.17	56.17	52.57	5.617	51.69	56.17	56.1
L1 norm	4.575e+06	4.575e+06	4.575e+06	3.681e+05	4.584e+06	4.575e+ 06	4.575e+ 06
L2 norm	2.446e+04	2.446e+04	2.363e+04	3255	2.355e+04	2.445e+ 04	2.445e+ 04
Max norm	255	255	247.5	106.3	273	255	257.9

Numerical image analysis incorporates the methodology that measures the image's numerical parameters based on the image's gray-level brightness. The mean value of an original brain MRI image is 69.8. The mean value 63.08 is achieved by combining up all pixel and partition by the total number of pixels. (total pixel = 157050).The median value of an original brain MRI image is 63 for original image and synthesis image but the reconstructed image's median value increased which is 73.In this theses paper the grayscale image's maximum value and minimum value lies o to 255. Hence the range is 255. But the reconstructed in approximations and detail image this value decreased and about 247.5 and 212.5.We have got the standard deviation same for original image and synthesis image and it's 65.25 where the mean value is 69.8.But for reconstructed in approximations and detail image this value decreases , 60 and 12.71 respectively. We get a lot of variance in reconstructed approximations and detail image. In a median absolute deviation parts the statistical value is dispersed. This value is more effective than standard deviation for outliers in a pixel set. By different norm value the images length, size can be characterized.

3.2.2 Compression Thresholding Method

The original image is compressed by 2D Wavelet transform. Before compressed the image the thresholding method is selected. The threshold is defined as the value in which information are deemed to be minimal sufficient to be set to zero [16]. There are 2 types of thresholding method we observed: global and by level thresholding method.

3.2.3 Global Thresholding

The default thresholding method is global thresholding method. Global thresholding includes of setting an intensity value (threshold) so that all vexes with an intensity value under the threshold contribute to one phase, while the remaining phase corresponds to the other. Global thresholding is as good as the step removed of intensity between the image's two peaks. Global thresholding can be computed as $t_g = 2\log(d_j)$ where d_j is the total number of wavelet coefficients [17].

- **Retained Energy and No of Zeros:** After compressed and decompressed, the amount of image's information retains is called the retained energy. The retained energy is balanced to the addition of the squares of the pixel values. If the retained energy is hundred percent then it is known as lossless and that means the image is reconstructed exactly [16]. Lossless compression occurs when the threshold value is set to 0,that means the detail is same. By changing value it causes the energy lost so this is defined as lossy compression. By increasing the threshold value the retained energy can be decreased but then the number of zeros is increased. On the other hand in a balance sparsity norm by increasing global thresholding value the compressed images size is smaller than original image. That means compression ratio is greater by increasing threshold value.

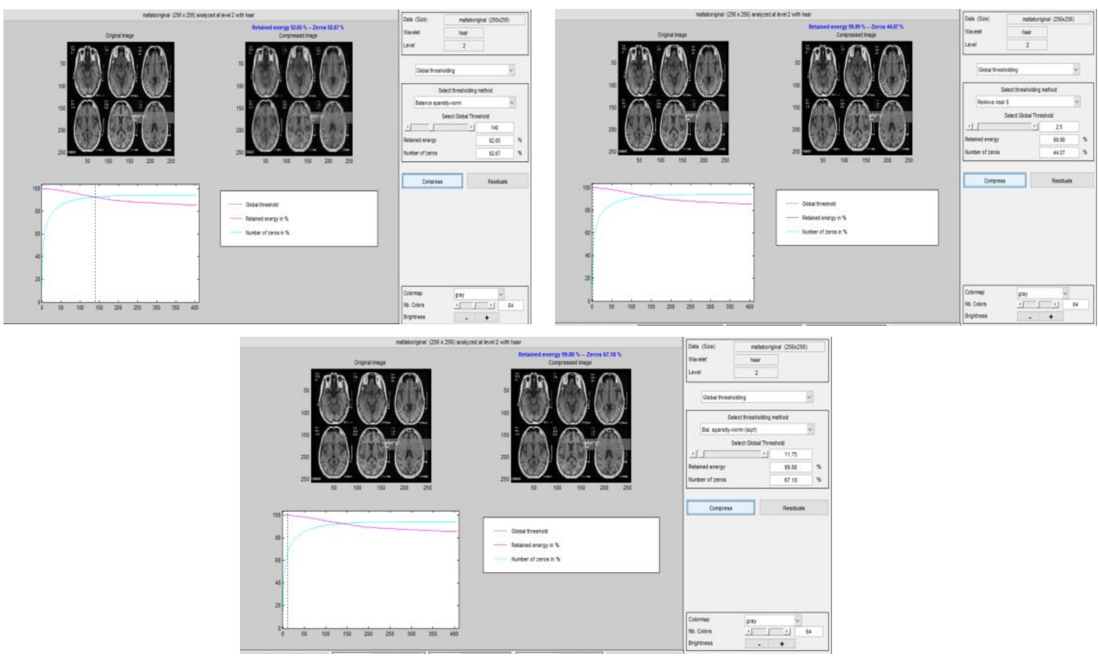


Figure 3.2 (d): Original Compressed Image by Balance sparsity-norm, Remove near-zero and Bal. sparsity-norm (sqrt.).

In the balance sparsity-norm sometimes decrease the matrix norm, balancing may increase the exactness of computed own values. In a balance sparsity-norm the retained energy is 92.65% and the no. of zeros is 92.67 % when the thresholding value is 140.In a balance sparsity-norm the compression image has lost energy and that means the compression ratio is better. In a re-move near zero the retained energy is 99.99% and no. of zeros is 44.07 % when the thresholding value is 2.5.In this method the image did not lost energy so retained energy is greater and no. of zeros is decreased. So it causes low compression ratio than balance sparsity-norm. Another global thresholding method, bal. sparsity-norm (sqrt.) express it's retained energy about 99.88% whereas the no. of zeros is 67.18% when the thresholding value is 11.75. It gives higher com-pressed image than remove near zero thresholding method. On the other hand in the above statistical table the value of standard deviation in a compressed image changes slightly which is 59.89 for balance sparsity norm and 65.25 is for remove near zero and 65.17 for bal. sparsity-norm (sqrt).The balance sparsity-norm gives lossy image which is seen in the above table. The changes value of this method is greater than other two method.

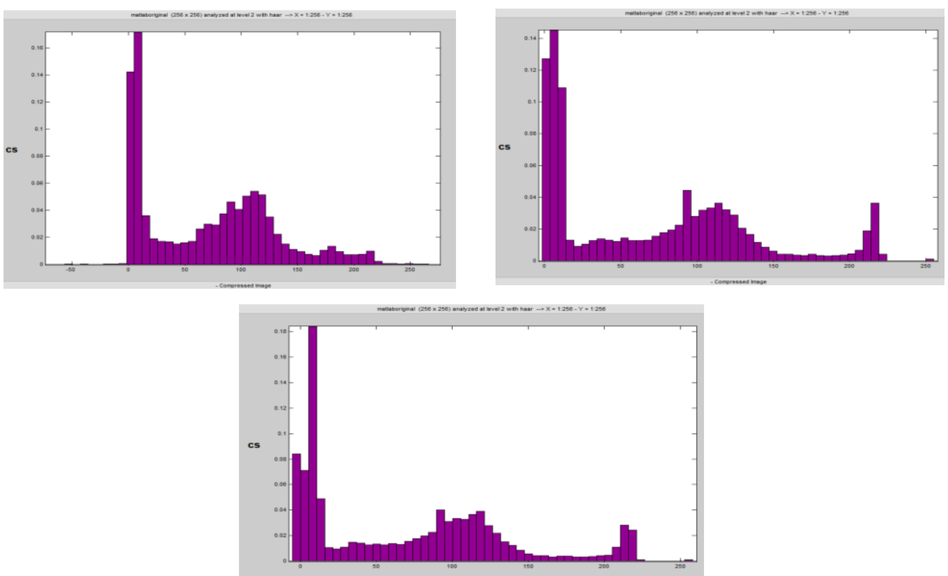


Figure 3.2(e): histogram of original brain MRI compressed by 3 thresholding method

According to the statistical value a line chart is drawn which express the variation of different value of original image and original compressed image.

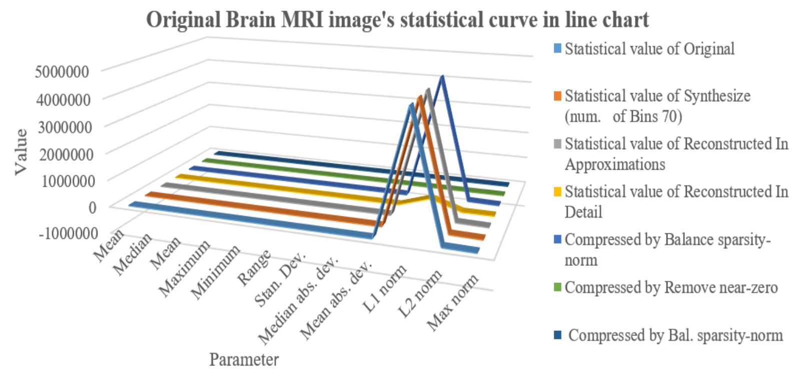


Figure 3.2 (f): Line chart representation of original brain MRI images statistical value

The line chart is a graph of data plotted using a series of lines. Line charts display horizontal lines across the map, with the values axis shown on the chart's left side. There is an ideal curve for Brain MRI image. The curve show in different database. A line chart is used to represent data over a continuous time span. There is data value between -1000000 to 5,000,000. That data is continuous represent mean 69.8 to max norm 255. The lowest pixel is 0 and highest pixel is l1 norm 4575000. The grayscale image of brain MRI intensity is 0 to 255.

3.3 Different Image Noise

Image noise is indiscriminately variation in image glossiness or color and is typically a component of electronic noise. Image noise can also come from film distortion and a perfect photon detector's unavoidable shot noise. In a general words a noise means unwanted signal or unwanted electrical fluctuation in an image. So it can be said that the pixels in the picture show different intensity. There are some of noise which is applicable for image. Some noise is described in below which is used.

3.3.1 Salt & Pepper Noise

Salt & Pepper noise is also called fixed value impulse noise. It can be caused by keen and abrupt fluctuations in the image signal. This presents itself as white and black pixels that sparsely arrive. An image that includes impulse noise will have dark pixels in bright areas and bright pixels in dark areas. Impulse noise is often found in medical image during transmission, storage and processing. Impulse noise's presence in clinical image can be high or low. That's why the noise degrades the quality of image and can hamper the image information detail. For a 8 bit gray scale image the typical value 0 for salt noise and 255 for pepper noise [18].

3.3.2 Gaussian Noise

It is also referred to as electronic noise as it arrives in amplifiers or detectors and also called amplifier noise. It is caused by ordinary sources such as nuclear torrid vibration and the discrete origin of hot body radiation. It disturbs the gray values in an image. The noise at each level is free of pixel quality strength. That is why Gaussian noise model has been developed by its PDF or normalizes histogram with respect to gray meaning in essence and characteristics [19].

$$P(x) = 1/\left(\sigma\sqrt{2\pi}\right) * e^{(x-\mu)^2} /2\sigma^{2\ -\infty<0<\infty} \qquad (10)$$

Where $P(x) =$ Gaussian distribution noise, $\sigma =$ standard deviation, $\mu =$ mean

3.3.3 Sinusoidal Noise

This noise is created by interference with electronics, particularly during image processing in the power signal. At multiples of specific frequencies, this noise has special properties such as spatially based and sinusoidal in nature. This occurs in the form of frequency domain related spots [20].

3.3.4 Speckle Noise

Speckle noise is a granular noise naturally present in the active radar and synthetic aperture radar (SAR) images and degrades their performance. Speckle noise in modern radar arises from random fluctuations in the return signal from an object not larger than a single element of image processing [21].

The original image is affected by these noises and the noisy images are given below:

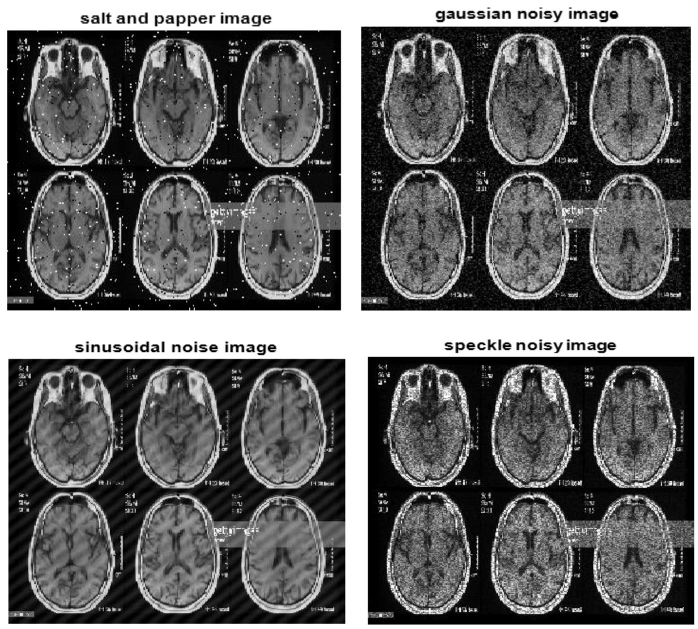


Figure 3.3: Noisy images

3.4 Statistical analysis and compression of Salt & Pepper Noisy image

The Salt and Pepper noise is also called data drop noise because numerically it drop the original data values. The Salt & Pepper noise is added with noise density 0.02 in original brain MRI image. The Salt & Pepper noisy image is taken .mat file and indexed by wavelet 2D.The image is first decomposed by four bands (LL, HL, LH and HH) at level 2 in Haar wavelet. Different statistical value and the histograms are taken respectively.

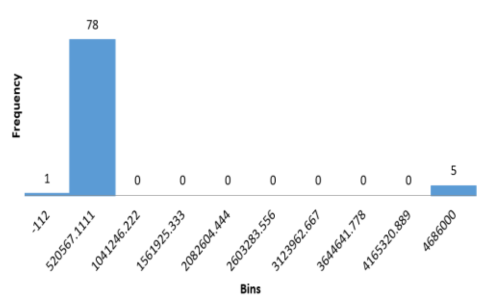


Figure 3.4 (a): Histogram of Salt & Pepper Noisy image

The above histogram is drawn by the value of Salt & Pepper noisy image's statistical parameter. The histogram represents the bins -112 to 520567 where the frequency distribution is high. There are total 79 frequency to count 84 and this value is so high for ideal image. The range between 1041246.222 to 416320.889, no frequency is present in the range that means no frequency is distributed in that range.

Now, the Salt & Pepper noisy image has been compressed just like figure 3.2(d). Here Different thresholding method has been selected during compression to get different values. Statistical analysis is a component of various data analysis and it express the data variance. So Different statistical value of Salt & Pepper noisy image is expressed below:

Table 3.4: Statistical analysis of the Salt & Pepper noisy image in wavelet tool

Parameter	Statistical value				Statistical value (Compress)		
	Original	Synthesize (Bins 70)	Reconstructed In Approximations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	70.86	70.86	70.85	0	70.86	70.86	70.86
Median	63	63	71.25	0	71.88	62.84	62.75
Mean	7.65	1.821	7.65	2.24	6.881	6.475	7.8
Maximum	255	255	255	112	290.4	256.3	260.5
Minimum	0	0	0	-112	-108.9	-1.25	-5.5
Range	255	255	255	224	399.4	257.5	266
Stan. Dev.	67.46	67.46	60.21	16.32	61.01	67.46	67.4
Med. abs. dev.	54	54	58	1.5	52.81	54.16	54.25
M. abs. dev.	57.57	57.57	52.01	7.583	52.3	57.57	57.52
L1 norm	4.644e+06	4.644e+06	4.644e+06	4.969e+05	4.686e+06	4.644e+06	4.644e+04
L2 norm	2.505e+04	2.505e+ 04	2.38e+04	4178	2.394e+04	2.505e+04	2.504e+04
Max norm	255	255	255	112	290.4	256.3	260.5

In the above table the variation of data is seen compare with original image. The mean value of Salt & Pepper noisy image is 70.86 which was 69.8 in the original image. By added noise we got these variance. The median value of Salt & Pepper noisy image is 63 for original image and synthesis image but the reconstructed image's median value increased which is 71.25. The maximum value and minimum value lies as previous table 0 to 255.But the detail image this value of range is decreased and about 224.We have got the standard deviation same for original image and synthesis image and it's 67.46 where the mean value is 70.86.But for reconstructed in approximations and detail image this value decreases, 60.21 and 16.32 respectively. In reconstructed approximations and detail image a lot of variance has been noticed. The statistical value of noisy compressed image vary due to select different thresholding method. In balance sparsity-norm the median is so changes (63 to 71.88). But the other method the value is almost similar. The standard deviation value is 61.01 which is also a great matter to understand how much information or data has been lost by this thresholding method. But ultimately the other thresholding method keeps its value identical. According to the statistical value a line chart is drawn which express the variation of different value of Salt & Pepper noisy image and compressed image.

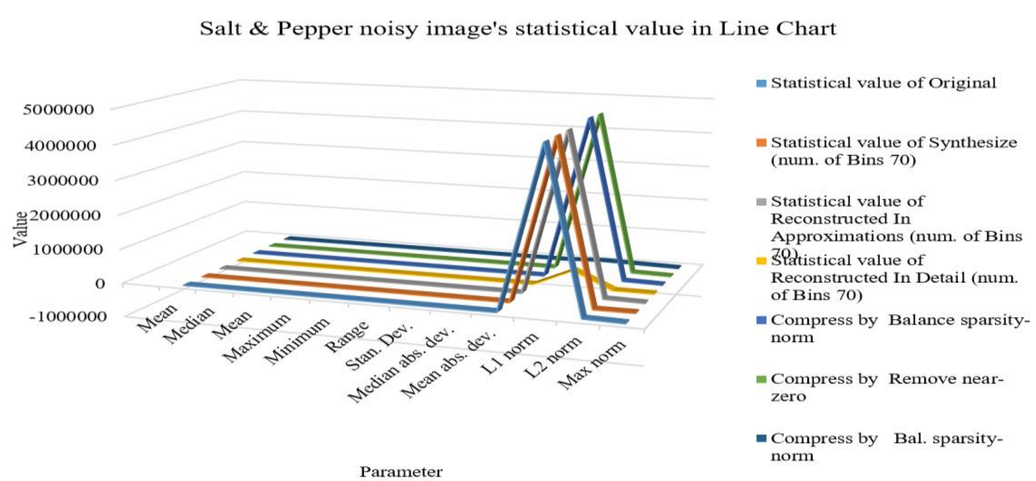


Figure 3.4 (b): Line chart representation of Salt & Pepper noisy image's statistical value

This curve shows the different data of the Salt & Pepper noisy image and compressed image. There is a range of value which is -1,000,000 to 5,000,000. That data is continuous represent with mean 70.86 to max. norm 255. The lowest pixel is 0 and highest pixel is L1 norm which is 4644000.

3.5 Statistical analysis and compression of Gaussian Noisy image

The Gaussian noise is added with mean 0 and variance 0.01 in original brain MRI image. The image is saved by .mat file format and indexed in Wavelet 2D. The image is first decomposed by four bands (LL, HL, LH and HH) at level 2 in haar wavelet. We have taken different statistical values and the histograms respectively.

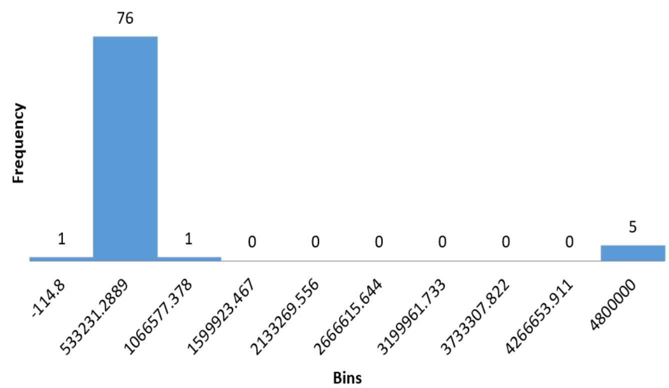


Figure 3.5 (a): Histogram of Gaussian Noisy image

The above histogram is drawn by the value of Gaussian noisy image's statistical parameter. The histogram represents the bins -114.8 to 4800000 where the frequency distribution is high in 533231.2889. There are total 76 frequency to count 84 and this value is so high for ideal Gaussian noisy image. The range between 1599923.467to 4266653.911, no frequency is present in the range that means no frequency is distributed in that range.

Now, the Gaussian noisy image has been compressed just like figure 3.2(d). Here Different thresholding method has been selected during compression to get different values.

In a balance sparsity-norm the retained energy of Gaussian noisy image is 90.89% and the no. of zeros is 90.90 % when the thresholding value is 110.The compression image has lost energy and that means the compression ratio is better. In a remove near zero the retained energy is 99.62% and no. of zeros is 45.05 % when the thresholding value is 16.5.The image did not lost energy and retained energy is almost 100% and the image is lossless. It is better than Salt & Pepper thresholding method remove near zero. The value of no. of zeros is decreased. So it causes low compression ratio than balance sparsity-norm. Another global thresholding method, bal. sparsity-norm (sqrt.)

express it's retained energy about 99.90% whereas the no. of zeros is 30.07% when the thresholding value is 10.5. The retained energy is similar with Salt & Pepper noisy compressed image in bal. sparsity-norm (sqrt).

To observe the variation in different data the statistical value of Gaussian noisy image is expressed below:

Table 3.5: Statistical analysis of the Gaussian noisy image in wavelet tool

Parameter	Statistical value				Statistical value(Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in approximations	Reconstructed in Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	72.97	72.97	72.97	0	72.97	72.97	72.97
Median	61	61	70	0	70.40	61	61
Mean	2.55	1.821	12.45	2.295	14.22	4.481	2.703
Maximum	255	255	249	114.8	295.8	266.6	261.9
Minimum	0	0	0	-114.8	-89.94	-15.25	-10.94
Range	255	255	249	229.5	385.8	281.9	272.8
Stan. Dev.	65.99	65.99	58.24	16.72	58.93	65.7	65.91
Med. abs. dev.	51	51	50.5	8.25	50.81	51.38	51.81
M. abs. dev.	55.48	55.48	50.16	11.55	49.99	55.34	55.45
L1 norm	4.782e+06	4.782e+06	4.782e+06	7.568e+05	4.795e+06	4.8e+06	4.793e+06
L2 norm	2.519e+04	2.519e+04	2.39e+04	4281	2.401e+04	2.514e+04	2.517e+04
Max norm	255	255	249	114.8	295.8	266.6	261.9

The mean value of Gaussian noisy image is 72.97 which was 69.8 in the original image and 70.86 in the Salt & Pepper noisy image. By added Gaussian noise we got these variance. The median value of Gaussian noisy image is 61 for original image and synthesis image but the reconstructed image's median value increased which is 70. The maximum value and minimum value lies as previous table 0 to 255.But the reconstructed in approximations range value is 249 and detail image this value is decreased and about 229.5.We have got the standard deviation same for original image and synthesis image and it's 65.99 where the mean value is 72.97.But for reconstructed in approximations and detail image this value decreases, 58.24 and 16.72 respectively. We get a lot of variance in reconstructed approximations and detail image. The statistical value of noisy compressed image vary due to select different thresholding method. In balance sparsity-norm the median is so changes (61 to 70.40). But the other method the value is similar. The standard deviation value is 58.93 which is also a great matter to understand how much information or data has been lost by this thresholding method. But ultimately the other thresholding method keeps its value almost similar.

According to the statistical value a line chart is drawn which express the variation of different value of Gaussian noisy image and compressed image.

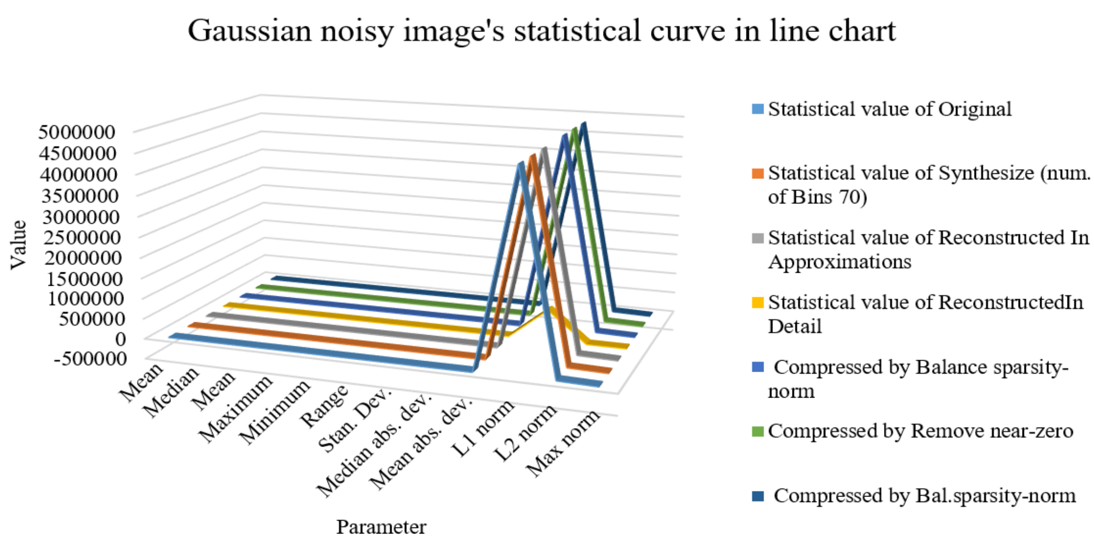


Figure 3.5 (b): Line chart representation of Gaussian noisy image's statistical value

Therre is range of value between -1000000 to 5,000,000. This data is continuous represent which has a mean 72.97 to max norm 255. The lowest pixel is 0 and highest pixel is L1 norm 4782000.

3.6 Statistical analysis and compression of Sinusoidal Noisy image

The Gaussian noise is added with mean 0 and variance 0.01 in original brain MRI image. The image is saved by .mat file format and indexed in Wavelet 2D. The image is first decomposed by four bands (LL, HL, LH and HH) at level 2 in haar wavelet. We have taken different statistical values and the histograms respectively.

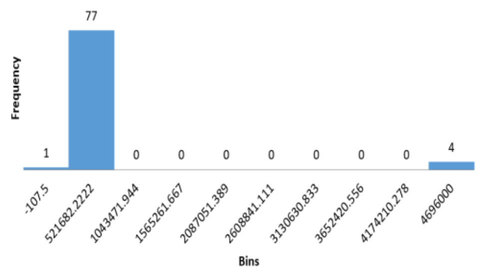


Figure 3.6(a): Histogram of Sinusoidal Noisy image

The above histogram is drawn by the value of Sinusoidal noisy image's statistical parameter. The histogram represents the bins -107.5 to 4696000 where the frequency distribution is high in 521682.2222. There are total 77 frequency to count 84 and this value is so high for ideal Sinusoidal noisy image. The range between 1043471.944 to 4174210.278, no frequency is present in the range that means no frequency is distributed in that range. Now, the Sinusoidal noisy image has been compressed just like figure 3.2(d). Here Different thresholding method has been selected during compression to get different values.

In a balance sparsity-norm the retained energy of Sinusoidal noisy image is 92.22% and the no. of zeros is 92.22 % when the thresholding value is 142.6.The compression image has lost energy and that means the compression ratio is good. In a remove near zero the retained energy is 99.97% and no. of zeros is 40.62 % when the thresholding value is 5.346.The image did not lost energy and retained energy is almost 100% and the image is lossless but the compression ratio is not better The value of no. of zeros is decreased. Another global thresholding method, bal. sparsity-norm (sqrt.) express it's retained energy about 99.82% whereas the no. of zeros is 62.53% when the thresholding value is 11.94. The retained energy is similar with Salt & Pepper noisy compressed image in bal. sparsity-norm (sqrt).

To observe the variation in different data the statistical value of Sinusoidal noisy image is expressed below:

Table 3.6: Statistical analysis of the Sinusoidal noisy image in wavelet tool.

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in approximations	Reconstructed in detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.8	69.8	69.8	0	69.8	69.8	69.8
Median	62.38	62.38	69.53	0	71.42	62.29	62.49
Mean	-6.096	15.83	-1.346	-2.151	9.784	-1.649	-2.571
Maximum	269.6	269.6	237.2	107.5	281.6	269.6	269.6
Minimum	-14.62	-14.62	-13.9	-107.5	-80.81	-15.93	-16.9
Range	284.2	284.2	251.1	215.1	362.4	285.6	286.5
Stan. Dev.	66.18	66.18	61.28	12.94	60.5	66.16	66.06
Med. abs. dev.	50.87	50.87	53.12	2.932	53.1	51.14	51.34
M. abs. dev.	56.51	56.51	52.98	6.572	52.03	56.5	56.44
L1 norm	4.696e+06	4.696e+06	4.682e+06	4.307e+05	4.654e+06	4.693e+06	4.682e+06
L2 norm	2.462e+04	2.462e+04	2.378e+04	3312	2.365e+04	2.462e+04	2.46e+04
Max norm	269.6	269.6	237.2	107.5	281.6	269.6	269.6

The mean value of Sinusoidal noisy image is 69.8 which is same with original image. By added Gaussian noise we got various variance. The median value of Sinusoidal noisy image is 62.38 for original image and synthesis image but the reconstructed image's median value increased which is 69.53.The maximum value and minimum value is totally changed in this noise. The range value for original image and synthesize image is 284.2. But the reconstructed in approximations range value is 251.1 and detail image this value is decreased and about 215.1.We have got the standard deviation same for original image and synthesis image and it's 66.18 where the mean value is

69.8.But for reconstructed in approximations and detail image this value decreases, 61.38 and 12.94 respectively. We get a lot of variance in reconstructed approximations and detail image.

The statistical value of noisy compressed image vary due to select different thresholding method. In balance sparsity-norm the median value is so changes (62.33 to 71.42.). But the other method the value is almost similar. The standard deviation value is 60.5 which is also a great matter to understand how much information or data has been lost by this thresholding method. But ultimately the other thresholding method keeps its value almost similar.

According to the statistical value a line chart is drawn which express the variation of different value of Sinusoidal noisy image and compressed image.

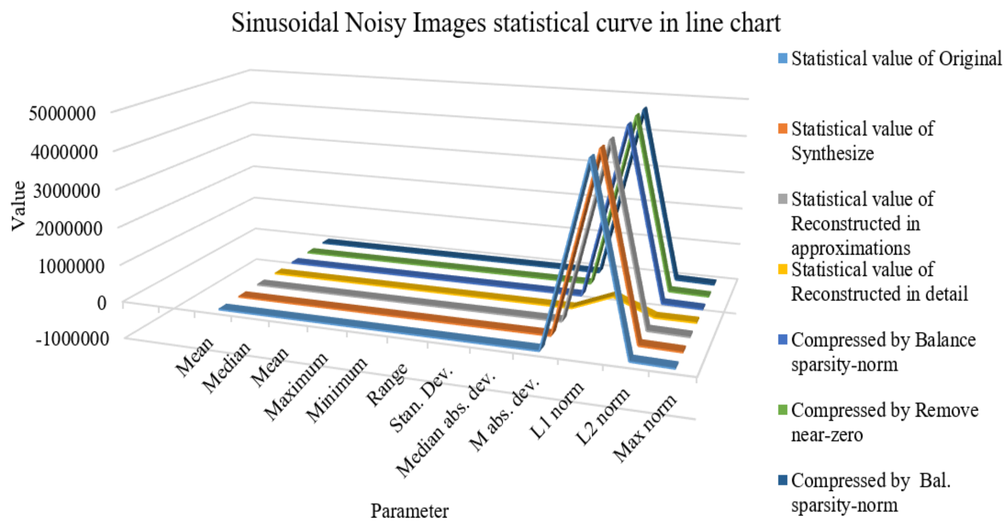


Figure 3.6 (b): Line chart representation of Sinusoidal noisy image's statistical value

This curve shows in different data of sinusoidal noisy image and compressed image. Negative value -1000000 to positive value 5,000,000 represents the data range. This is a continuous represent with mean 69.8 to max norm 255. The lowest pixel is 0 and highest pixel is L1 norm 4696000.

3.7 Statistical analysis and compression of Speckle Noisy image

The speckle noise is added to brain MRI original image with noise density 0.09.Then the image is saved by .mat file format and indexed it in Wavelet 2D. The noisy image is first decomposed by four bands in Haar wavelet with level 2. The histogram is taken to compare with other noisy images.

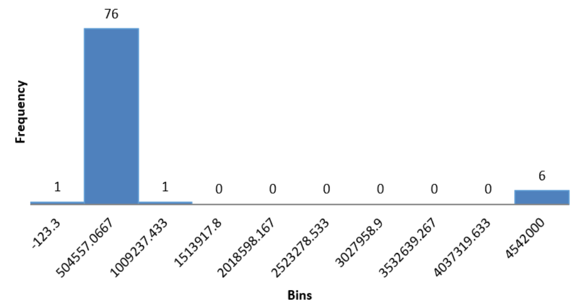


Figure 3.7(a): Histogram of Speckle Noisy image

The above histogram is drawn by the value of Speckle noisy image's statistical parameter. The histogram represents the bins -123.3 to 4542000 where the frequency distribution is high in 504557.0667. There are total 76 frequency to count 84 and this value is so high for ideal Speckle noisy image. The range between 1513917.8 to 4037319.663,no frequency is present in the range that means no frequency is distributed in that range. Now, the Speckle noisy image has been compressed by Wavelet 2D transform just like figure 3.2(d). Here Different thresholding method has been selected during compression to get different values.

The retained energy of Speckle noisy image is 90.55% and the no. of zeros is 90.56 % in the balance sparsity norm thresholding method when the thresholding value is 105.The compression image has lost energy and the compression ratio is good. In a remove near zero the retained energy is 99.94% and the no. of zeros is 45.56 % when the thresholding value is 10.The image did not lost energy and retained energy is almost 100% and the image is lossless but the compression ratio is not better. The value of no. of zeros is decreased than balance sparsity-norm thresholding method. Another global thresholding method, bal. sparsity-norm (sqrt.) express it's retained energy about 99.93% whereas the no. of zeros is 46.14% when the thresholding value is 10.25. The retained energy is almost similar with remove near zero thresholding method.

To observe the variation in different data the statistical value of Speckle noisy image is expressed below:

Table 3.7: Statistical analysis of the Speckle noisy image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (num. of Bins 70)	Recon-structed in approxima-tions	Recon-structed in detail	Balance sparsity-norm	Remove near-zero	Bal. spar-sity-norm
Mean	69.09	69.09	69.09	0	69.09	69.09	69.09
Median	54	54	68.5	0	67.88	54	54
Mean	2.55	1.821	7.65	2.465	3.161	9.056	9.056
Maximum	255	255	255	123.3	304.4	261.9	261.9
Minimum	0	0	0	-123.3	-86.81	-4.25	-4.25
Range	255	255	255	246.5	391.2	266.1	266.1
Stan. Dev.	68.86	68.86	60.42	17.96	61.99	68.82	68.82
Median abs. dev.	48	48	57.75	4.75	55.94	47.25	47.25
M. abs. dev.	57.41	57.41	52.36	10.83	52.57	57.38	57.38
L1 norm	4.528e+06	4.528e+06	4.528e+06	7.099e+05	4.542e+06	4.528e+06	4.528e+06
L2 norm	2.497e+04	2.497e+04	2.35e+04	4598	2.376e+04	2.495e+04	2.495e+04
Max norm	255	255	255	123.3	304.4	261.9	261.9

The mean value of Speckle noisy image is 69.09 which is same with original image and sinusoidal noisy image. By added Speckle noise various variance is observed in its pixel value. The median value of Sinusoidal noisy image is 54 for original image and synthesize image but the reconstructed image's median value increased which is 68.5 which is also similar with sinusoidal noisy image. The maximum value and minimum value is same with original image in this noise but only change in compressed image. The range value for original image and synthesize image is 255. But in detail image this value is decreased and about 246.5. The standard deviation value is same for original image and synthesis image and it's 68.86 where the mean value is 69.9.But for reconstructed in approximations and detail image this value decreases, 60.42 and 17.46 respectively. A lot of variance is expressed by reconstructed approximations and detail image.

The statistical value of noisy compressed image vary due to select different thresholding method. In balance sparsity-norm the median value is so changes (54 to 67.88.). But the other method the value is identical. The standard deviation value is 61.99 in balance sparsity-norm thresholding method which is also a great matter to understand how much information or data has been lost by this thresholding method. In remove near zero and bal. sparsity-norm (sqrt.) method the standard deviation value is almost same as original image and it is 68.82.The other statistical parameter's value also depends on the thresholding value. If the thresholding value is changed heavily then the Median Absolute Deviation, Mean Absolute Deviation and other parameter's value changed also with a big difference.

A line chart is drawn by following the statistical value of above table.

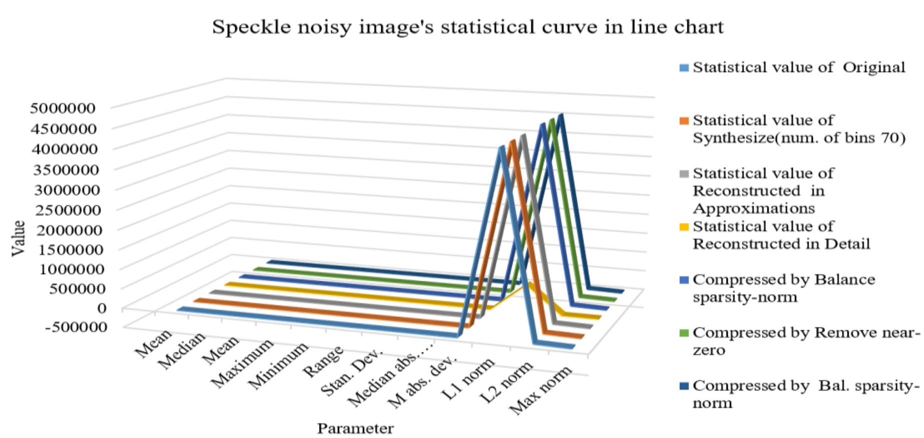


Figure 3.7 (b): Line chart representation of Speckle noisy image's statistical value

This curve represents the different statistical value of Speckle noisy and compressed image. Range of the value contains between -1000000 to 5,000,000. That is continuous represent with mean 69.09 to max norm 255. The lowest pixel is 0 and highest pixel is l1 norm 4528000.

CHAPTER 4

BRAIN MRI IMAGE DE-NOISING

De noising is a significant task in image analysis especially in clinical application. It is a significant technique in which the original image is restored by removing the unwanted signal or data. The formal goal of de noising is to preserve the necessary data in an image.

4.1 De noising techniques

There are basic three types de noising technique in image processing. They are: Spatial domain filtering, Transform domain filtering and Wavelet Thresholding method. Since in this project the spatial domain filtering is used so spatial domain filtering method is described in below.

4.1.1 Spatial domain filtering

Spatial filtering is traditional way to remove unwanted signal from an image. There are two types of spatial filter: Linear filter and Non Linear filter.

4.1.1.1 Linear model filters

In the presence of signal-dependent noise, linear filters often tend to blur sharp edges, kill lines and other fine image information and perform badly. The speed is the great advantage of linear models and the models are not capable of preserve edges of the images in an effective behavior. So the edges are smeared out which are recognized as discontinuities in the image [21]. The Mean filter, Wiener filter and Gaussian filter are the examples of linear model filters.

4.1.1.2 Non Linear model filters

When there is a multiplicative and function based noise comes to an image then the non-linear filters play a significant role to reduce the noise. The non-linear models are capable to preserve the edges in a proper way. It can handle edges better than linear models [21]. In a non-linear filter, the noise is filtered without trying to explicitly classify it. Spatial filters use low-pass filtering on pixel groups assuming the noise occupies the higher frequency spectrum area. **U**sually, spatial filters eliminate noise to a logical extent but at the expense of blurring images, rendering the edges of pictures turbid in turn [22].

4.2 Median Filter

It's a non-linear filter. It is done by searching the value of median by across the window. After that substitute the pixel median value of each entry in the window. If the window has an odd number of participants, it is easy to define the median. The filter is robust. Median filters used to ensure smooth processing of images and time series. The benefit of using this filter is that it is far less sensitive to severe (called outliers) values than the mean. Such outliers can be eliminated without increasing image keenness [22].

4.3 Wiener Filter

It's linear filter that is based on statistical approach to remove noise from a noisy image. It can filter from different angle. The wiener filtering technique requires the noise spectrum and original signal details and only works well if the fundamental signal is smooth. Signal and noise are static linear with known spatial properties [23]. Wiener method incorporates spatial thinning and the selection of window size corresponds to its system complexity command [22].

4.4 Linear Filter

Linear filtering is such kind of filtering where the resulting pixel value is a linear mixture of the pixel values in the community of the input pixel. In the existence of signal-dependent noise, linear filters often appear to blur keen edges, damage lines and other detailed image information, and perform sickly [24].

4.5 Gaussian Filter

Gaussian filter is a good overall-purpose filter and the latest structured approach to separating the elements of roughness and waviness from a primary layer [25].Gaussian filtering system is based on the detection of maximum. It is also linear filter with low pass capability. The degree of keenness in this filter is controlled by σ .If σ is larger then it causes the high keenness in image [26].

4.6 Statistical analysis and compression of de-noised image by Median filter

The median filter has been used in noisy images to get de-noised images. The image has been compressed by thresholding method and different compressed value is indexed in the given statistical table and the retained energy, no. of zeros of the image is also calculated to describe the image after compress.

Table 4.6(a): Statistical analysis of the Salt & Pepper de-noised image in wavelet tool

Parameter	Statistical value				Statistical value(Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approximations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.18	69.18	69.18	0	69.18	69.18	69.18
Median	68	68	72.25	0	72.56	68.81	68
Standard Deviation	63.03	63.03	60.61	10.03	58.51	62.75	62.93
Median abs. dev.	57	57	58.25	0.75	55	57.25	57.13
Mean abs. dev.	54.52	54.52	52.77	3.953	51.08	54.25	54.43

After de noising the salt & pepper noisy image used median filter the statistical value has been changed. The mean value of salt & pepper noisy image is 70.86 which is decreased and in de-noised image it is 69.18. The mean value of de-noised image is identical with original brain MRI image. The mean value is reconstructed perfectly. The median value of de-noised image is increased but the most notifying thing is standard deviation. The value of standard deviation in de-noised image is nearly similar with original image. In original image it is 65.25 which is 67.46 in noisy image. But after de noising the value comes similar and it is 63.03.The median filter gives better performance to reconstruct the image as we observed in this statistical table. The image has been compressed by three thresholding method the variance between retained energy in different thresholding method is calculated. The thresholding value can change the measurement of lossy or lossless information in the image.

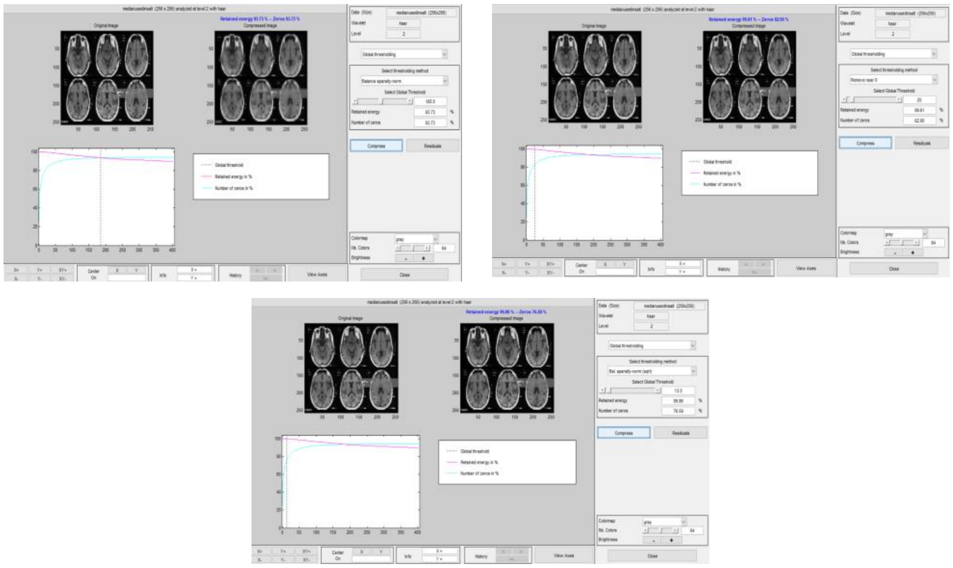


Figure 4.6 (a): Salt & Pepper de-noised Compressed Image by Balance sparsity-norm, Remove near-zero and Bal. sparsity-norm (sqrt.).

Compressed Value of Salt & Pepper De-noised compressed image by median filter in three thresholding method:

<u>Balance Sparsity-norm:</u>	<u>Remove near zero:</u>	<u>Bal. sparsity-norm (sqrt):</u>
Thresholding value- 185.5	Thresholding value- 25	Thresholding value- 13.5
Retained energy- 93.75%	Retained energy- 99.61%	Retained energy- 99.86%
No. of zeros- 93.75 %	No. of zeros- 82.95 %	No. of zeros- 76.59 %

Table 4.6(b): Statistical analysis of the Gaussian de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Recon-structed in Approxima-tions	Recon-structed in Detail	Balance sparsity-norm	Remove near-zero	Bal. spar-sity-norm
Mean	70.02	70.02	70.02	0	70.02	70.02	70.02
Median	68	68	72	0	73.44	68	68.25
Stan. Dev.	60.35	60.35	58.1	9.678	55.49	60.33	60.15
Med. abs. dev.	52	52	52.5	2.75	51.38	52	52.75

Mean abs. dev.	51.96	51.96	50.45	5.2777	48.62	51.95	51.86

The mean value of Gaussian noisy image is 72.97 which is decreased and in de-noised image it is 70.02. The mean value of de-noised image is almost same with original brain MRI image. The mean value is reconstructed almost perfectly. The median value of de-noised image is increased but the most notifying thing is standard deviation. The value of standard deviation in de-noised image is 60.35 where as in noisy image it is almost 67. A variation is noticed in standard deviation. Then the image is compressed by three thresholding method and the variance between retained energy in different thresholding method is observed.

Compressed Value of Gaussian De-noised compressed image by median filter in different thresholding method:

Balance Sparsity-norm:

Thresholding value-194

Retained energy- 93.42%

No. of zeros- 93.42%

Remove near zero:

Thresholding value - 5

Retained energy- 99.97 %

No. of zeros- 41.82 %

Bal. sparsity-norm (sqrt):

Thresholding value- 14

Retained energy- 99.72%

No. of zeros- 70.07%

Table 4.6 (c): Statistical analysis of the Sinusoidal de-noised image in wavelet tool

Parameter	Statistical value				(Statistical value(Compressed)		
	Original	Synthesize. (Bins 70)	Reconstructed in Approximations	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.18	69.18	69.18	0	69.18	69.18	69.18
Median	67	67	70.75	0	72.41	67.15	67.23
Stan. Dev.	63.45	63.45	61.04	10.07	58.61	63.44	63.29
Med. abs. dev.	52.38	52.38	52.85	2.474	53.22	52.21	52.53
Mean abs. dev.	54.47	54.47	52.77	4.849	50.97	54.47	54.39

After de noising the Sinusoidal noisy image used median filter the variation of statistical value is observed. The mean value of Sinusoidal noisy image is 69.8 which is almost same in de-noised image it is 69.18. The mean value of de-noised image is almost same with original brain MRI image. The mean value is reconstructed almost perfectly. The median value of de-noised image is increased but the most notifying thing is standard deviation. The value of standard deviation in de-noised image is 63.45 where as in noisy image it is almost 66.18 for original image and in balance sparsity-norm the value is decreased and it is 60.5. In a de-noised image the standard deviation of balance sparsity -norm is less than noisy image and original brain MRI image.

The image has been compressed by three thresholding method the variance between retained energy is observed in different thresholding method.

Value of Sinusoidal De-noised compressed image by median filter in different thresholding method:

<u>Balance Sparsity-norm:</u>	<u>Remove near zero:</u>	<u>Bal. sparsity-norm (sqrt):</u>
Thresholding value-190.6	Thresholding value- 3.55	Thresholding value- 13.8
Retained energy-93.30%	Retained energy- 99.99%	Retained energy-99.97%
No. of zeros- 93.30%	No. of zeros-39.48%	No. of zeros- 72.84%

Table 4.6(d): Statistical analysis of the Speckle de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthe-size (num. of Bins 70)	Recon-structed in Approxima-tions	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	65.4	65.4	65.4	0	65.4	65.4	65.4
Median	62	62	66.5	0	68.66	62	62.28
Stan. Dev.	59.2	59.2	56.83	9.888	54.87	59.2	59.09
Med. abs. dev.	53	53	55.25	1.75	53.41	53	53.09
Mean abs. dev.	51.26	51.26	49.66	5.115	48.26	51.26	51.18

After de noising in the Speckle noisy image the variation of statistical value appears. The mean value of Speckle noisy image is 69.09 which is almost same with original brain MRI image but in de-noised image it decrease and it is 65.4.There is an information loss in de noising used median filter in speckle noisy image. The median value of de-noised image is increased but the most notifying thing is standard deviation. The value of standard deviation in de-noised image is 59.2 whereas in noisy image it is 68.86 for speckle noisy image and in balance sparsity-norm the value is decreased and it is 61.99 in speckle noisy image. In de-noised image the standard deviation value for balance sparsity-norm is 54.87.In a de-noised image the standard deviation of balance sparsity -norm is less than noisy image and original brain MRI image.

Then the image has been compressed by three thresholding method and we observe the variance between retained energy in different thresholding method. The thresholding value can change the measurement of lossy or lossless information in the image

Value of Speckle De-noised compressed image by median filter in different thresholding method:

<u>Balance Sparsity-norm:</u>	<u>Remove near zero:</u>	<u>Bal. sparsity-norm (sqrt):</u>
Thresholding value-52.8	Thresholding value-3	Thresholding value- 16.75
Retained energy-93.65%	Retained energy-99.99%	Retained energy- 99.68%
No. of zeros- 93.65%	No. of zeros-43.80%	No. of zeros- 73.22%

4.7 Statistical analysis and compression of de-noised image by Wiener Filter

The de noise image is saved by .mat file format and it is indexed by wavelet tool. The image is then compressed by three thresholding method and different compressed value is indexed in the above statistical table and the other compressed value is given below which describes the images condition after compress. The wiener filter is used in noisy images get de-noised images. The de-noised images have also different statistical parameters and we these images have been compressed which is given below.

Table 4.7 (a): Statistical analysis of the Salt & Pepper de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approximations	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	71.22	71.22	71.22	0	71.22	71.22	71.22
Median	74	74	77.25	0	76.69	74	74.38
Stan. Dev.	57.92	57.92	55.18	9.615	55.74	57.91	57.79
Med. abs. dev.	50	50	48.63	1.25	48.81	50	50.38
Mean abs. dev.	49.94	49.94	48.1	4.184	48.4	49.94	49.86

The Wiener filter is used in Salt & Pepper noisy image and it creates different statistical variation in de-noised reconstructed image. The mean value of de-noised image is 71.22 which is 70.86 in noisy image. The mean value is increased in de-noised image. On the other hand the median value of de-noised image is greater than original brain MRI image and Salt & Pepper noisy image. The value of standard deviation of de-noised image is smaller than original brain MRI image and Salt & Pepper noisy image.

The image has been compressed by three thresholding method and the variance is observed between retained energy in different thresholding method. The thresholding value can change the measurement of lossy or lossless information in the image

Value of Salt & Pepper De-noised compressed image by wiener filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-80.5	Thresholding value- 2	Thresholding value- 13.5
Retained energy- 97.07	Retained energy- 100	Retained energy- 99.83
No. of zeros- 91.40	No. of zeros- 42.01	No. of zeros- 74.75

Table 4.7 (b): Statistical analysis of the Gaussian de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approximations	Reconstructed in Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	73.23	73.23	73.23	0	73.23	73.23	73.23
Median	73	73	76.75	0	78.09	73.25	73.88
Stan. Dev.	55.73	55.73	53.06	9.286	50.58	55.72	55.56
Med. abs. dev.	49	49	47.25	1.75	44.88	48.88	48.75
Mean abs. dev.	47.64	47.64	45.97	4.414	44.14	47.63	47.52

The Wiener filter does not play an important role to de noise the Gaussian noisy image. The mean value of Gaussian de-noised image is 73.23 which is greater than original brain MRI image and almost similar with noisy image. The median value of de-noised image is greater than noisy image and original brain MRI image. On the other hand the standard deviation of original brain MRI image is 65.17 whereas in the noisy image the value is 65.99 but it decreased in de-noised image. The median absolute deviation and mean absolute deviation also make variation in this section. Then the image is compressed by three thresholding method and the variance is observed between retained energy in different thresholding method. The thresholding value can change the measurement of lossy or lossless information in the image.

Value of Gaussian De-noised compressed image by wiener filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-203.5	Thresholding value-2.5	Thresholding value-14.25
Retained energy- 93.54%	Retained energy- 99.99%	Retained energy- 99.78%
No. of zeros- 93.54%	No. of zeros- 41.74%	No. of zeros-75.11%

Table 4.7 (c): Statistical analysis of the Sinusoidal de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approximations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	70.2	70.2	70.2	0	70.2	70.2	70.2
Median	72.23	72.23	75.46	0	76.39	72.2	72.23
Stan. Dev.	59.32	59.32	56.79	9.256	54.47	59.32	59.32
Med. abs. dev.	51.89	51.89	50.5	1.932	48.03	51.88	51.89
Mean abs. dev.	50.95	50.95	49.32	4.318	47.68	50.94	50.95

The mean value of original brain MRI image is 69.8 and sinusoidal noisy image it is almost same but in de-noised image the value is changed. The median value of original brain MRI image is 63 but in noisy image it is 62.38 but in de-noised image it increase and about 72.23. The standard deviation of original brain MRI image is 65.25 whereas in noisy image it is 66.18 but in de-noised image it 59.32 and for balance sparsity-norm it decrease due to compress the image. The others value of this statistical analysis is also different than noisy and original image. Then the image has been compressed by three thresholding method. The thresholding value can change the measurement of lossy or lossless information in the image.

Value of Sinusoidal De-noised compressed image by wiener filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value- 189	Thresholding value- 2.90	Thresholding value- 13.75
Retained energy- 93.46%	Retained energy- 99.99%	Retained energy- 99.78%
No. of zeros- 93.46%	No. of zeros- 39.91%	No. of zeros- 75.47%

Table 4.7 (d): Statistical analysis of the Speckle de-noisedimage in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approxi-mations	Recon-structed in Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.58	69.58	69.58	0	69.58	69.58	69.58
Median	72	72	75.5	0	76.59	72	72.56
Stan. Dev.	58.21	58.21	55.22	10.07	53.46	58.21	58.09
Median abs. dev.	50	50	49.5	1.5	47.22	50	49.56
Mean abs. dev.	49.76	49.76	48.23	4.713	47.06	49.76	49.68

The Wiener filter is used to de noise the speckle noisy image and there are a lot of differences observed in the statistical table. The mean value of original brain MRI image is 69.8 but for noisy image the value is 69.09. In this case the mean value is identical with original brain MRI image. The median value of speckle noisy image is 54 but in reconstructed in approximations the value increase. In this de-noised image the median value is bigger than original brain MRI image and noisy image. The standard deviation of this de-noised image is 58.21 for original and 55.22 for reconstructed in approximation and due to compress the standard deviation value reduced. The image has been compressed and the variance of different retained energy is discussed below. The thresholding value can change the measurement of lossy or lossless information in the image

Value of Speckle De-noised compressed image by wiener filter in different thresholding method:

<u>Balance Sparsity-norm:</u>

Thresholding value-165.2

Retained energy- 93.56%

No. of zeros- 93.56%

<u>Remove near zero:</u>

Thresholding value-2

Retained energy-100 %

No. of zeros- 43.02 %

<u>Bal. sparsity-norm (sqrt):</u>

Thresholding value- 12.75

Retained energy- 99.83 %

No. of zeros- 72.48 %

4.8 Statistical analysis and compression of de-noised image by Linear Filter

The Linear filter is used in noisy images to get de-noisedimages. The de-noised images have also different statistical parameters and these values are given below in a tabular form.

Table 4.8 (a): Statistical analysis of the Salt & Pepper de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approxima-tions	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	72.23	72.23	72.23	0	72.23	72.23	72.23
Median	18	18	63.75	0	51	17	16.59
Stan. Dev.	85.39	85.39	67.34	26.42	75.06	85.35	85.33
Med. abs. dev.	18	18	56.75	4	46.63	17	16.59
Mean abs. dev.	73.23	73.23	57.46	14.07	62.68	73.21	73.2

In the above table the statistical parameter gives the various difference due to use linear filter. The mean value of de-noised image is so much larger than noisy and original brain MRI image. But the miracle is that the median value of de-noised image is so much smaller than original image and noisy image. The mean value of de-noised image is 72.23 whereas in noisy image it is 70.86 and for original image it is 69.8. The median value of de-noised image is 18 for original image and it increase when the image is compressed by balance sparsity-norm but for remove near-zero and bal. sparsity norm (sqrt.) the value is almost same for original image and synthesis image. The standard deviation value for original image is 85.39 and for balance sparsity-norm it is 75.06 whereas for noisy image the value is 67.46 and for balance sparsity-norm it is 61.01. Due to this kind of huge variation the linear filter increases the de-noised images size.

Then the image has been compressed by three thresholding method and the variance of retained energy is calculated in different thresholding method.

Value of Salt & Pepper De-noised compressed image by wiener filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-127.5	Thresholding value-9	Thresholding value- 11.25
Retained energy- 86.72%	Retained energy-99.95 %	Retained energy- 99.93 %
No. of zeros- 88.51%	No. of zeros- 44.44 %	No. of zeros- 47.62 %

Table4.8 (b): Statistical analysis of the Gaussian de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approxi-mations	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	85.42	85.42	85.42	0	85.42	85.42	85.42
Median	47	47	76.75	0	52.25	41.63	47
Stan. Dev.	95.04	95.04	58.66	39.74	76.83	93.06	95.02
Med. abs. dev.	47	47	44.75	24.5	35.13	44.37	47
Mean abs. dev.	83.44	83.44	48.9	30.27	64.55	81.35	83.42

Just like the previous table the linear filter gives the extra abnormalities in the Gaussian de-noised image and that's why the de-noised image's size is increased above the noisy image. Then the image is compressed by three thresholding method and we observe the variance between retained energy in different thresholding method.

Value of Gaussian De-noised compressed image by Linear filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-127	Thresholding value-52.5	Thresholding value- 11.25
Retained energy- 80.83%	Retained energy-97.72 %	Retained energy- 99.97 %
No. of zeros- 82.27%	No. of zeros- 47.69 %	No. of zeros- 14.46 %

Table 4.8 (c): Statistical analysis of the Sinusoidal de-noisedimage in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approximations	Recon-structed In Detail	Balance sparsity-norm	Remove near-zero	Bal. spar-sity-norm
Mean	85.42	85.42	85.42	0	85.42	85.42	85.42
Median	47	47	76.75	0	52.25	41.63	47
Stan. Dev.	95.04	95.04	58.66	39.74	76.83	93.06	95.02
Med. abs. dev.	47	47	44.75	24.5	35.13	44.37	47
Mean abs. dev.	83.44	83.44	48.9	30.27	64.55	81.35	83.42

In the above table the mean value is huge changed than original brain MRI image and noisy image in spite of compression the image in various thresholding method. The same incident happens in the standard deviation, median standard deviation and mean standard deviation. That's why the image gets extra bits and it is caused to increase the file size. Then the image has been compressed and the variance between retained energy in different method is observed.

Value of Sinusoidal De-noised compressed image by Linear filter in different thresholding method:

Balance Sparsity-norm:

Thresholding value-220

Retained energy- 87.64%

No. of zeros- 87.64%

Remove near zero:

Thresholding value-13.61

Retained energy-99.91 %

No. of zeros- 41.86 %

Bal. sparsity-norm (sqrt):

Thresholding value- 14.83

Retained energy- 99.89%

No. of zeros- 43.80 %

Table 4.8 (d): Statistical analysis of the Speckle de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed in Approxi-mations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.83	69.83	69.83	0	69.83	69.83	69.83
Median	9	9	63.75	0	28.78	9.5	8.5
Stan. Dev.	97.19	97.19	64.03	39.3	83.61	96.99	97.14
Med. abs. dev.	9	9	56.5	10.75	28.78	9.5	8.5
Mean abs. dev.	83.66	83.66	56.01	25.26	70.42	83.58	83.65

The linear filter is not appropriate for de noise this image because in the above statistical data it is seen that the mean, median, standard deviation, median absolute deviation, mean absolute deviation value is increased or decreased randomly which causes the inappropriateness in this process.

Value of Speckle De-noised compressed image by Linear filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-130.8	Thresholding value-23.5	Thresholding value- 11.5
Retained energy- 82.85%	Retained energy-99.73 %	Retained energy- 99.94%
No. of zeros- 82.85%	No. of zeros- 46.44 %	No. of zeros- 35.88 %

4.9 Statistical analysis and compression of de-noised image by Gaussian Filter

The de noise image is saved by .mat file format and it is indexed by wavelet tool. The image is then compressed by three thresholding method and different compressed value is indexed in the above statistical table and the other compressed value is given below which describes the images condition after compress.

Table 4.9(a): Statistical analysis of the Salt & Pepper de-noised image in wavelet tool

Parameter	Statistical value				Statistical value(Compressed)		
	Original	Synthesize (Bins 70)	Reconstructed In Approximations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	70.97	70.97	70.97	0	70.97	70.97	70.97
Median	72	72	73.75	0	75.69	71.63	71.75
Standard Dev.	60.11	60.11	57.69	9.652	55.29	60.11	60.01
Median Abs. D.	58	58	52.5	1.5	49.25	58.13	57.88
Mean Abs. D.	51.91	51.91	50.09	5.088	48.3	51.91	51.82

The mean value of Salt & Pepper noisy image is 70.86, median value is 63 for original and in a compressed image the value is 71.88 for balance sparsity-norm and 62.84 for remove near zero and 62.75 for bal. sparsity-norm (sqrt.). But in this case the mean value is also similar with noisy image and median value is increased with respect to noisy image. The standard deviation value is 60.11 which is smaller than noisy image. The image is reconstructed with necessary information.

The image has been compressed and the variance between retained energy in different thresholding method measures the compression performance in the image.

Statistical Value of Salt & Pepper De-noised compressed image by Gaussian filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-160.5	Thresholding value-2.5	Thresholding value- 12.75
Retained energy- 93.57%	Retained energy-100 %	Retained energy- 99.86%
No. of zeros- 93.56%	No. of zeros- 43.38 %	No. of zeros- 67.14 %

Table 4.9 (b): Statistical analysis of the Gaussian de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthe-size (num. of bins 70)	Recon-structed In Approxi-mations	Recon-structed In Detail	Balance spar-sity-norm	Remove near-zero	Bal. spar-sity-norm
Mean	73.05	73.05	73.05	0	73.05	73.05	73.05
Median	70	70	73.25	0	76	70.06	70.63
Stan. Dev.	58.22	58.22	55.67	9.679	52.96	58.17	58
Median abs. dev.	51	51	50.5	4	48.5	50.69	51.47
Mean abs. dev.	50.12	50.12	48.16	6.277	46.03	50.1	50.02

The mean value of Gaussian noisy image is 72.97, median value is 61 for original and in a compressed image the value is 70.40 for balance sparsity-norm and 61 for remove near zero and bal. sparsity-norm (sqrt.). The value of standard deviation of de-noised image 58.22 which is smaller than noisy image and for noisy it is 65.99.But when the image is compressed in balance sparsity-norm then the value for de-noised image is 52.96 which is 59.89 for brain MRI original image.

The Gaussian de-noised image used by Gaussian filter has been compressed and the retained energy, no. of zeros has also been discussed in the below.

Compressed Value of Gaussian De-noised compressed image by Gaussian filter in different thresholding method:

Balance Sparsity-norm:	Remove near zero:	Bal. sparsity-norm (sqrt):
Thresholding value-171	Thresholding value-6.5	Thresholding value- 13
Retained energy- 93.30%	Retained energy-99.94 %	Retained energy- 99.71%
No. of zeros- 93.30%	No. of zeros- 42.21 %	No. of zeros- 63.14 %

Table 4.9 (c): Statistical analysis of the Sinusoidal de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (bins 70)	Reconstructed in Approxi-mations	Recon-structed in Detail	Balance spar-sity-norm	Remove near-zero	Bal.spar-sity-norm
Mean	69.8	69.8	69.8	0	69.8	69.8	69.8
Median	69.9	69.9	72.35	0	74.82	69.82	70.24
Stan. Dev.	61.2	61.2	59.07	8.97	56.33	61.18	61.03
Med. abs. dev.	53.21	53.21	52.69	2.787	51.23	53.07	53.26
Mean abs. dev.	52.88	52.88	51.18	5.184	49.06	52.87	52.78

The mean value of original brain MRI image is 69.8 as we have seen before. After de noise the sinusoidal noisy image the value is identical that means the image is reconstructed with its valuable information. The median value of de-noised image is huge as compare with original brain MRI image and sinusoidal noisy image. The standard deviation of de-noised image is changed in original image and de-noised image. It is changed so much in balance sparsity-norm thresholding method which gives high compression ratio.

The Sinusoidal de-noised image used by Gaussian filter has been compressed and the retained energy, no. of zeros has also been discussed to compare with the noisy compressed image.

Compressed Value of Sinusoidal De-noised compressed image by Gaussian filter in different thresholding method:

Balance Sparsity-norm:

Thresholding value-185.7

Retained energy- 93.37%

No. of zeros- 93.37%

Remove near zero:

Thresholding value-4.44

Retained energy-99.98 %

No. of zeros- 40.05 %

Bal. sparsity-norm (sqrt):

Thresholding value- 13.63

Retained energy- 99.76%

No. of zeros- 69.08 %

Table 4.9 (d): Statistical analysis of the Sinusoidal de-noised image in wavelet tool

Parameter	Statistical value				Statistical value (Compressed)		
	Original	Synthesize (bins 70)	Reconstructed In Approximations	Reconstructed In Detail	Balance sparsity-norm	Remove near-zero	Bal. sparsity-norm
Mean	69.2	69.2	69.2	0	69.2	69.2	69.2
Median	68	68	71.75	0	73.94	68.5	68.75
Stan. Dev.	60.38	60.38	57.81	10.14	55.63	60.37	60.28
Med. abs. dev.	57	57	57	3	51.72	57.75	57.75
Mean abs. dev.	52.28	52.28	50.41	6.047	48.81	52.27	52.2

The mean value of this de-noised image is almost similar with original indexed image and speckle noisy image. The median value of de-noised image is 68 which is 63 for original indexed image and 54 for speckle noisy image. There is a great variation in the value of mean. On the other hand the median value for original indexed image is 63 which is changed in this de-noised image. The standard deviation is also changed compare with the analysis of original and noisy and de-noised image.

The Speckle de-noised image used by Gaussian filter has been compressed and the retained energy, no. of zeros has also been discussed to compare with the noisy compressed image.

Compressed Value of Speckle De-noised compressed image by Gaussian filter in different thresholding method:

<u>Balance Sparsity-norm:</u>

Thresholding value-136.3

Retained energy- 93.47%

No. of zeros- 93.48%

<u>Remove near zero:</u>

Thresholding value-4.5

Retained energy-99.98 %

No. of zeros- 44.20 %

<u>Bal. sparsity-norm (sqrt):</u>

Thresholding value- 11.75

Retained energy- 99.85%

No. of zeros- 60.89 %

CHAPTER 5

RESULT AND ANALYSIS

The outcomes and different analyzing results in this project is described in this chapter. The very popular method of image processing and signal processing is DWT which is used to compressed MRI image in this project and analysis with different parameter.

5.1 Implementation of noises in original brain MRI image

Different noises has been discussed in chapter 3. We get four types of noise which is implemented in MATLAB code by MATLAB R2018a Software with various noise density. Salt & Pepper noise is added with 0.02 noise density and Gaussian noise is added with mean 0 and variance 0.01 and Sinusoidal noise and Speckle noise is also added. The noisy images is given below:

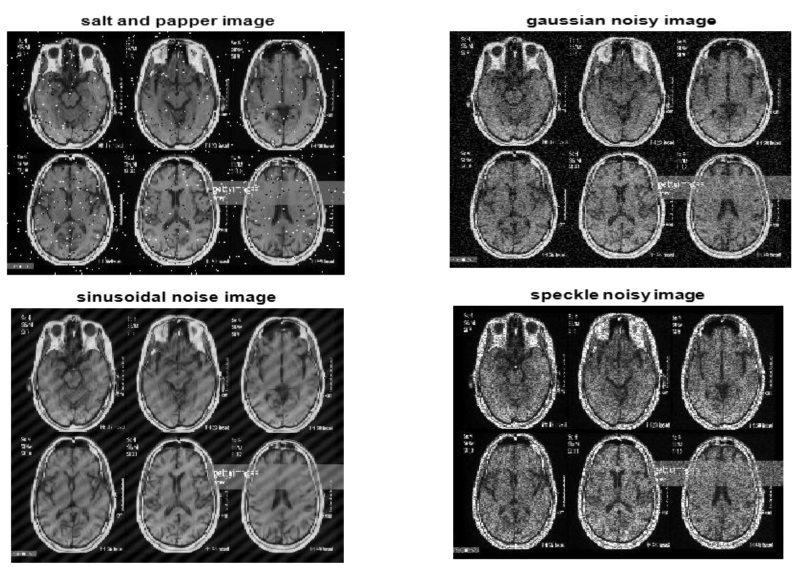


Figure 5.1 (a): Different Noisy image

5.1.1 Comparison of original, noisy and compressed image with compression ratio

The Original brain MRI image size is 19.0 KB in grayscale. By adding different noises we get various noisy images which images carry extra information or data. These unusual information or extra intensity is called noises.

Table 5.1.1 (a): Size of the Noisy Images

Noisy Images Size			
Salt &Pepper	Gaussian	Sinusoidal	Speckle
24.5 KB	30.0 KB	21.2 KB	24.8 KB

Whereas the original image is 19.0 KB. So By added Salt & Pepper noise the image size has been increased with extra 5.5 KB, added Gaussian noise the size has been increased with 11 KB and Sinusoidal noise has been increased extra 2.2 KB and Speckle noise has been enhanced extra 5.8 KB.

The original brain MRI image is compressed by different thresholding method with different thresholding value. In a balance sparsity-norm the thresholding value is 140 and in remove near zero it is 2.5 and in bal. sparsity-norm (sqrt.) it is 11.75. These compressed images are given below:

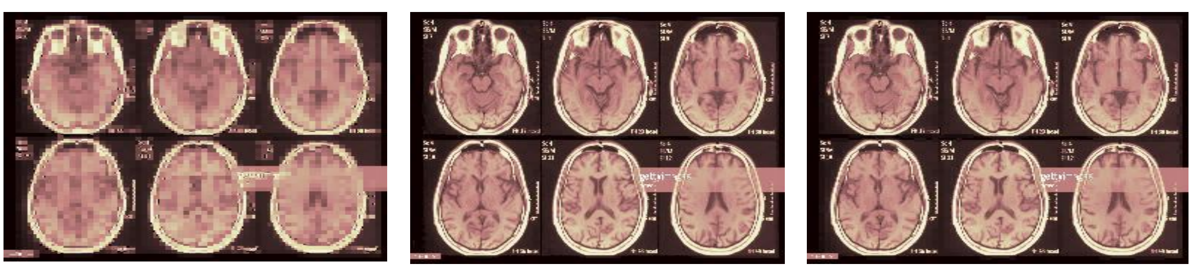


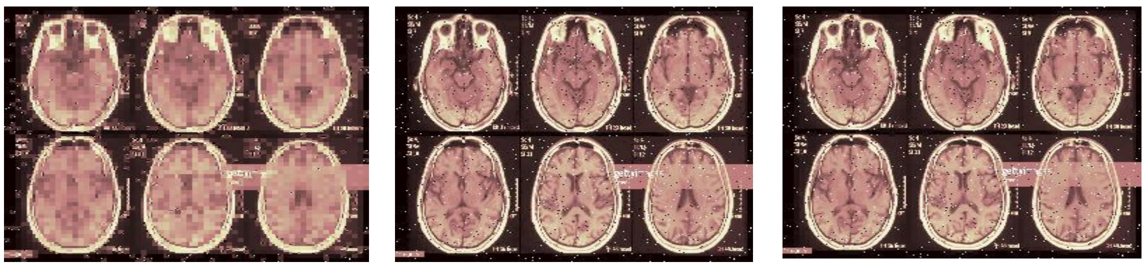
Figure 5.1.1 (b): Original Brain MRI Compressed image

Size of the original brain MRI Compressed image based on thresholding Method:

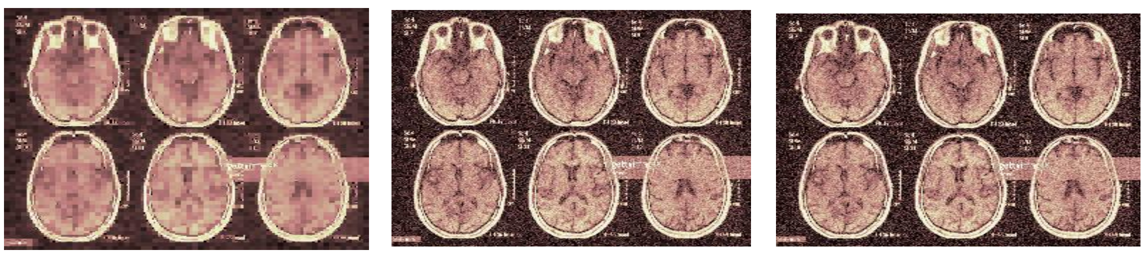
Table 5.1.1 (b): Size of original brain MRI Compressed image

Thresholding Method	Thresholding Value	Compressed Image Size
Balance Sparsity-norm	140	15.0 KB
Remove near-zero	2.5	18.7 KB
Bal. Sparsity-norm(sqrt)	11.75	18.3 KB

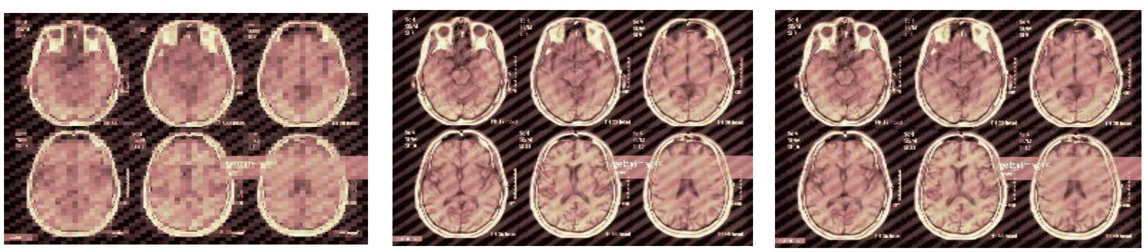
The noisy images are compressed by different thresholding method with different thresholding value. The noisy compressed images are given below:



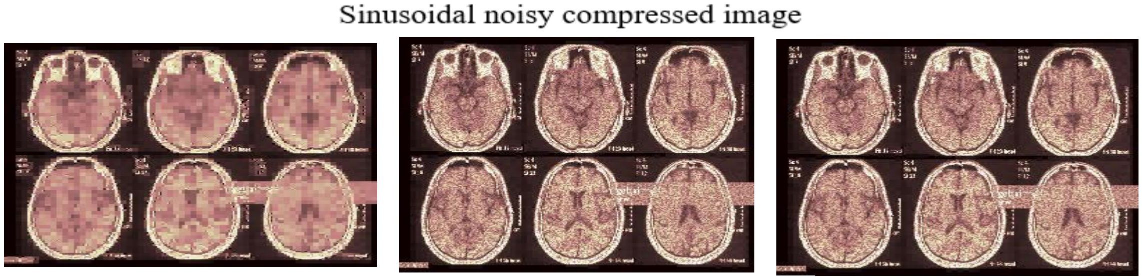
Salt & Pepper noisy compressed image



Gaussian noisy compressed image



Sinusoidal noisy compressed image



Speckle noisy compressed image

Figure 5.1.1 (c): Different noisy compressed image

Table 5.1.1 (c): Noisy Compressed images size based on thresholding method

Thresholding Method	Thresholding Value	Compressed image size
Salt & Pepper Noisy Image		
Balance sparsity-norm	124	18.2 KB
Remove near-zero	3	24.4 KB
Bal. sparsity-norm	11.75	24.1 KB
Gaussian Noisy Image		
Balance sparsity-norm	110	17.0 KB
Remove near-zero	16.5	29.1 KB
Bal. sparsity-norm	10.5	29.7 KB
Sinusoidal Noisy Image		
Balance sparsity-norm	142.6	18.3 KB
Remove near-zero	5.346	21.2 KB
Bal. sparsity-norm	1.94	21.6 KB
Speckle Noisy Image		
Balance sparsity-norm	105	17.4 KB
Remove near-zero	10	23.9 KB
Bal. sparsity-norm	10.25	23.9 KB

In the above table as we can see the compressed image size depends on the thresholding method. Each thresholding method characterizes the compressed image by retained energy and no. of zeros. If an image retained energy is far about 100 % then the image is lossy. It means it does not reconstructed perfectly with necessary information. The thresholding value is increased then it is seen that the image's size is reduced. Then it can give better compression ratio. But a good compression ratio can cause the loss of information. Since medical image is very sensitive for necessary information then the compression ratio will have to more noticeable. On the other hand the remove near-zero and bal. sparsity-norm (sqrt.) keeps its thresholding value less than 15 then the images retained energy is almost 100% that means it reconstructed perfectly with necessary information and lossless. But then the compression ratio will be poor.

5.1.2 Compression ratio of noisy compressed image

The compression ratio which is observed by the proportion of original image and compressed image. It is quantified as Cr=n1/n2, where n1 and n2 indicates the number of information or data carrying bits in the original image and the compressed image. The compression ratio is used by comparing the size of the original image and compressed image. So, we can be said that basically compression ratio (CR) as the ratio between the number of nonzero elements in the original matrix and the number of nonzero elements in the transformed matrix modified.

For Salt & Pepper noisy compressed image:

Balance sparsity-norm $= \frac{24.5}{18.2} = 1.34$

Remove near-zero $= \frac{24.5}{24.4} = 1.00$

Bal. sparsity-norm $= \frac{24.5}{24.1} = 1.01$

For Gaussian noisy compressed image:

Balance sparsity-norm $= \frac{30.3}{17} = 1.78$

Remove near-zero $= \frac{30.3}{29.1} = 1.04$

Bal. sparsity-norm $= \frac{30.3}{29.7} = 1.02$

For Sinusoidal noisy compressed image:

Balance sparsity-norm $= \frac{21.2}{18.3} = 1.15$

Remove near-zero $= \frac{21.2}{21.2} = 1$

Bal. sparsity-norm $= \frac{21.2}{21.6} = 0.98$

For Speckle noisy compressed image:

$$\text{Balance sparsity-norm} \quad = \frac{24.8}{17.4} = 1.42$$

$$\text{Remove near-zero} = \frac{24.8}{23.9} = 1.03$$

$$\text{Bal. sparsity-norm} \quad = \frac{24.8}{23.9} = 1.03$$

By analysis the result of compression ratio it can be said that in every analysis the balance sparsity norm thresholding method gives higher ratio. But in other thresholding the ratio is also good because in other method the image restored without loss any information. For medical image it is very much important.

5.2 Analysis on de-noised image

There are four types of filters are used in our project. We choose these filters in every noise and we want to try find out the best filters in specific noise though it is defined by many researchers. But we have tried to find out proper filters agree with the other existing method.

By using these filters in every noisy image we can see the different de-noised image which is given below. Salt & Pepper De-noised image which is de noised by Median filter, Wiener Filter, Linear Filter and Gaussian Filter respectively:

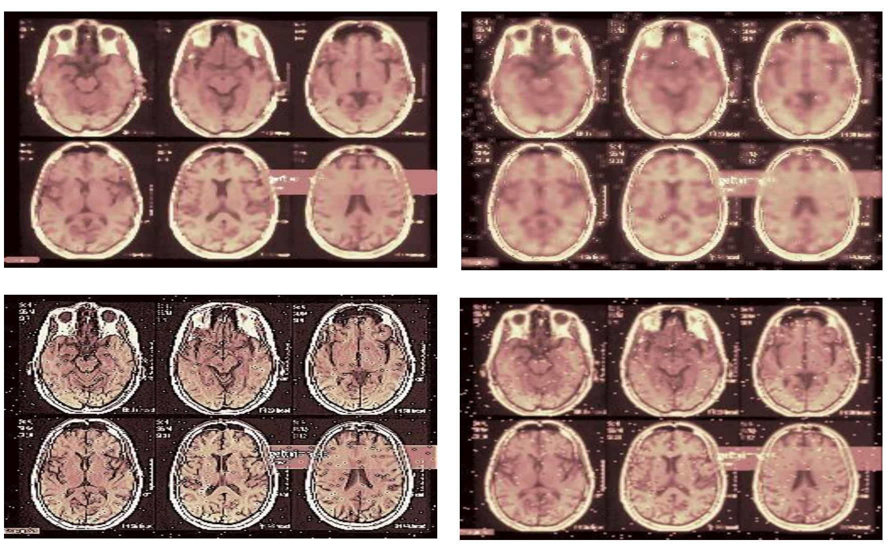


Figure 5.2 (a) : Salt & Pepper Denoisy image used Median, Wiener,Linear and Gaussian Filter

Gaussian De-noised image which is de noised by Median filter, Wiener Filter, Linear Filter and Gaussian Filter respectively:

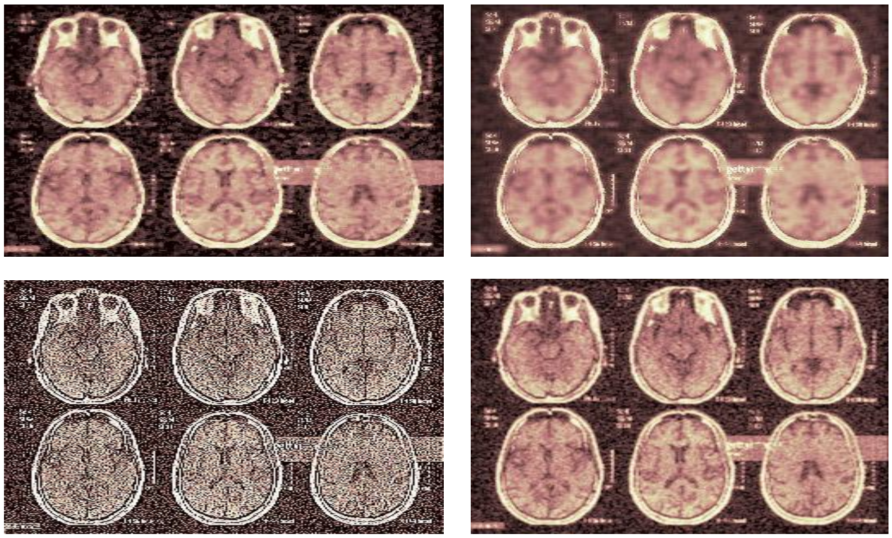


Figure 5.2 (b) : Gaussian Denoisy image used Median, Wiener,Linear and Gaussian Filter

Sinusoidal De-noised image which is de noised by Median filter, Wiener Filter, Linear Filter and Gaussian Filter respectively:

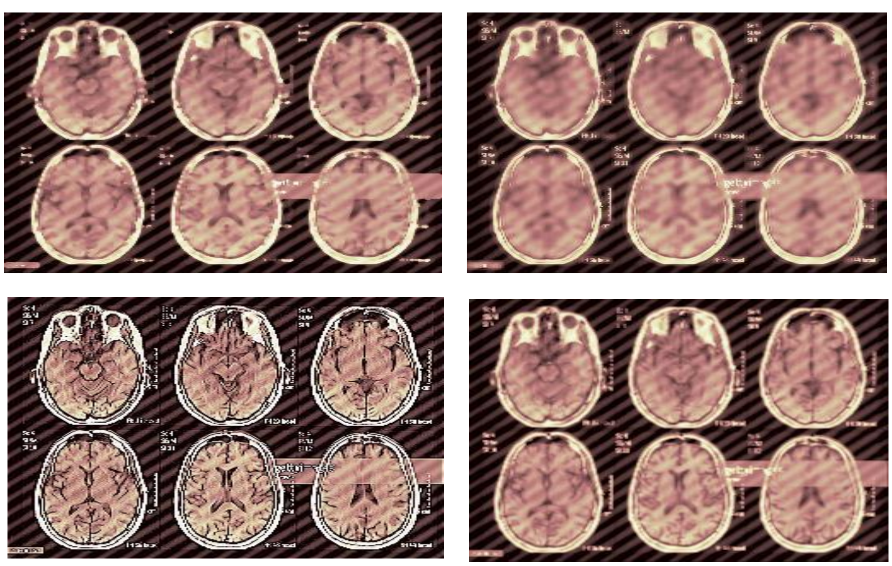


Figure 5.2 (c) : Sinusoidal Denoisy image used Median, Wiener,Linear and Gaussian Filter

Speckle De-noised image which is de noised by Median filter, Wiener Filter, Linear Filter and Gaussian Filter respectively:

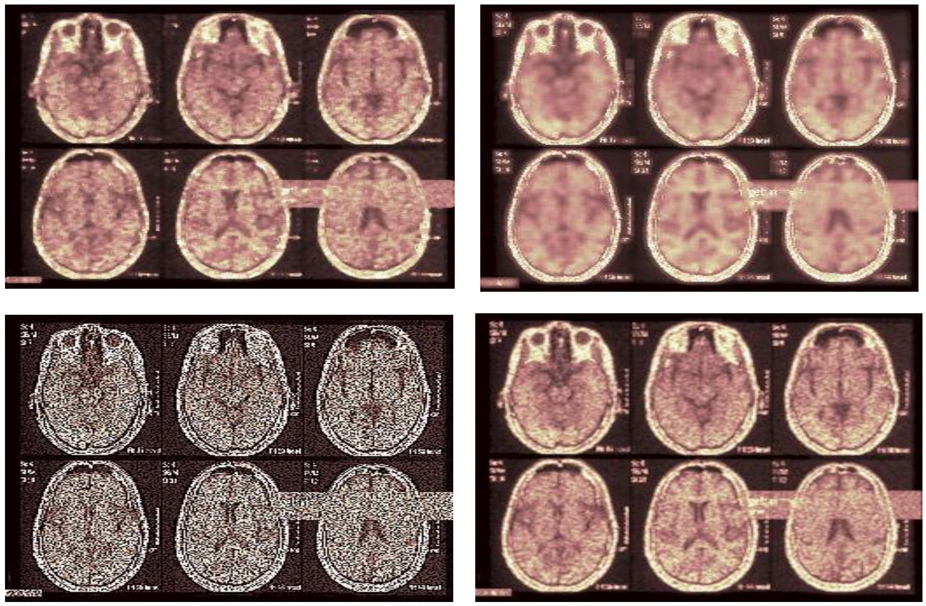


Figure 5.2 (d) : Speckle Denoisy image used Median, Wiener,Linear and Gaussian Filter

5.2.1 Performance analysis of Filter

A filter is not the right choice for each noisy image. A special filter gives better performance for a specific noisy image. A statistical value describe the information of the image. So the statistical value which is described in the chapter 4 is needed to find out the better filter performance. After de noising with specific filter we take standard deviation, median absolute deviation, mean absolute deviation value to understand the reconstructed image properties. Then it is easy to find out the performance of filter.

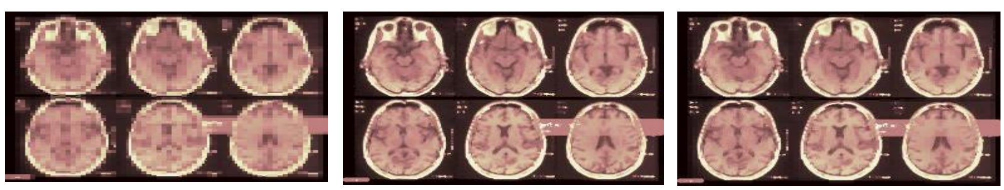
Table 5.2.1: Performance analysis of filter

Parameter	Original brain MRI Image	Salt & Pepper de-noised image	Gaussian de-noised image	Sinusoidal de-noised image	Speckle de-noised image
Median filter					
Standard Dev.	65.25	57.92	55.73	59.32	58.21
M. Abs. Dev.	54	50	49	51.89	50
Mean. A. Dev.	54.52	49.94	47.64	50.95	49.76
Wiener filter					
Standard Dev.	65.25	57.92	55.73	59.32	58.21
M. Abs. Dev.	54	50	49	51.89	50
Mean. A. Dev.	54.52	49.94	47.64	50.95	49.76
Linear filter					
Standard Dev.	65.25	85.39	95.04	128.5	97.19
M. Abs. Dev.	54	18	47	55.12	9
Mean. A. Dev.	54.52	73.23	83.44	93.73	83.66
Gaussian filter					
Standard Dev.	65.25	60.11	58.22	61.2	60.38
M. Abs. Dev.	54	58	51	55.12	57
Mean. A. Dev.	54.52	51.91	50.12	52.88	52.28

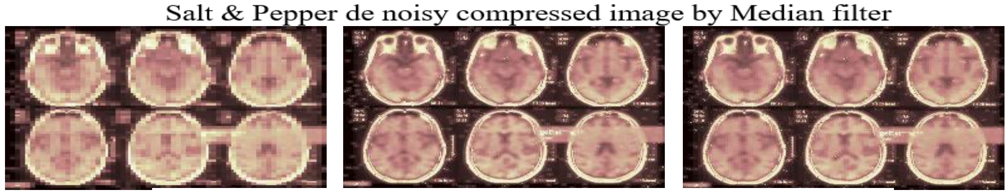
The salt & Pepper noise is a white and black pixels which is a keen and sudden disturbances in image. In the above filter the median filter has given the maximum reduction of noise. The standard deviation value of median filter for Salt & Pepper noise is nearly similar with original brain MRI image. After de noising the image reconstructed with its approximation with very minimal loss. So median filter is best for Salt & Pepper noisy image in our project. The wiener filter has given good performance for Salt & Pepper noisy image. In a Gaussian noisy image the standard deviation value for median filter, wiener filter and Gaussian filter is looking perfect compare with original image. So it is assumed for Gaussian image, the Median filter and Gaussian filter has given good performance. The linear filter is not the right choice to de noise the MRI image. The standard deviation value as it is seen in the above table is so high than the original brain MRI image also the median absolute deviation is very low in different noise and mean absolute deviation is high. This filter carry extra information when it de noise. So the image size is also big than the compressed and uncompressed image. For sinusoidal noisy image the median filter and wiener filter can be the better choice and finally for Gaussian noisy image the Gaussian filter, Median filter can be the right choice.

5.2.2 Analysis on de-noised compressed image

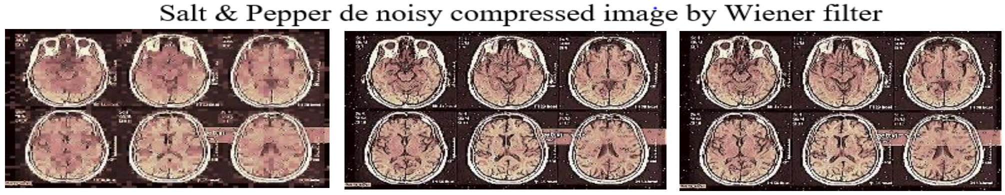
The de-noised images are compressed and the size of the de-noised images after compression is very noticeable to analysis. The images describes the variance with other compressed image in this project. Salt & Pepper de-noised compressed images are given below:



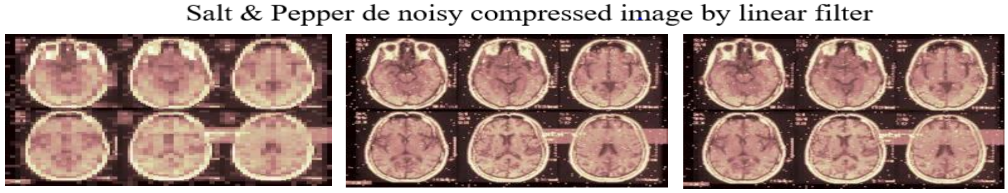
Salt & Pepper de noisy compressed image by Median filter



Salt & Pepper de noisy compressed image by Wiener filter



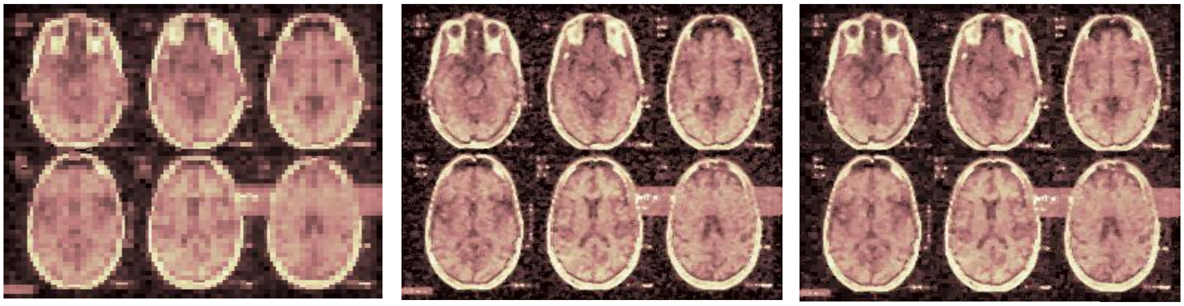
Salt & Pepper de noisy compressed image by linear filter



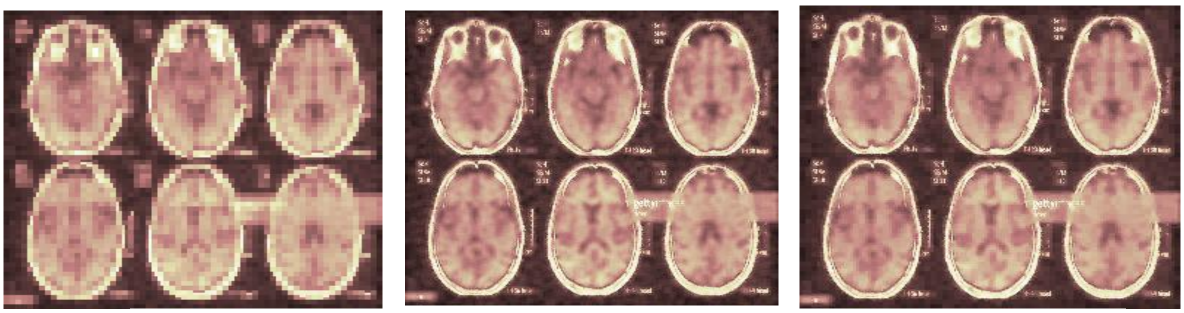
Salt & Pepper noisy compressed image by Gaussian filter

Figure 5.2.2 (a): Salt & Pepper de-noisedcompressed image by differnt filter

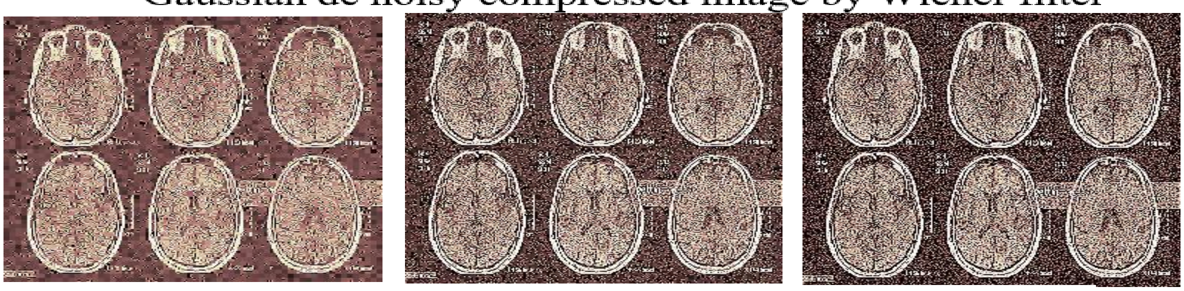
Gaussian de-noised compressed images are given below:



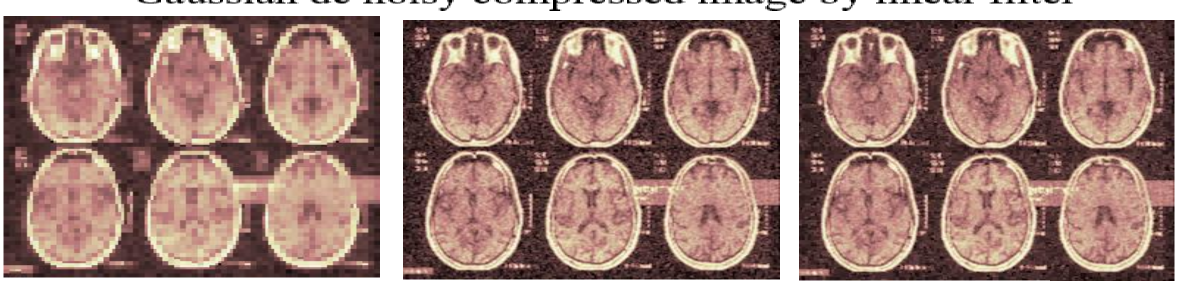
Gaussian de noisy compressed image by Median filter



Gaussian de noisy compressed image by Wiener filter



Gaussian de noisy compressed image by linear filter



Gaussian de noisy compressed image by Gaussian filter

Figure 5.2.2 (b): Gaussian de-noisedcompressed image by differnt filter

Sinusoidal de-noised compressed images are given below:

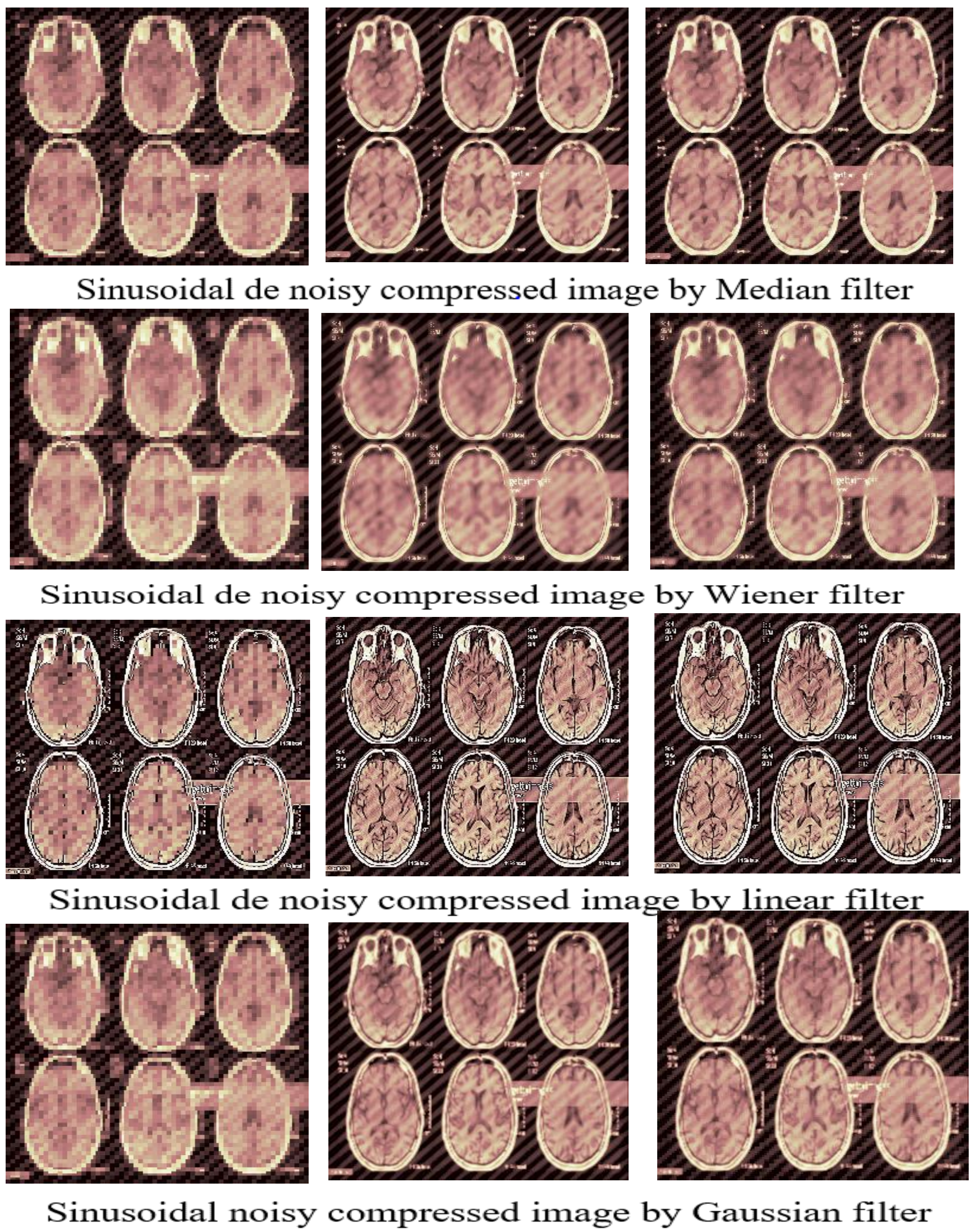


Figure 5.2.2 (c): Sinusoidal de-noised compressed image by differnt filter.

Speckle de-noised compressed images are given below:

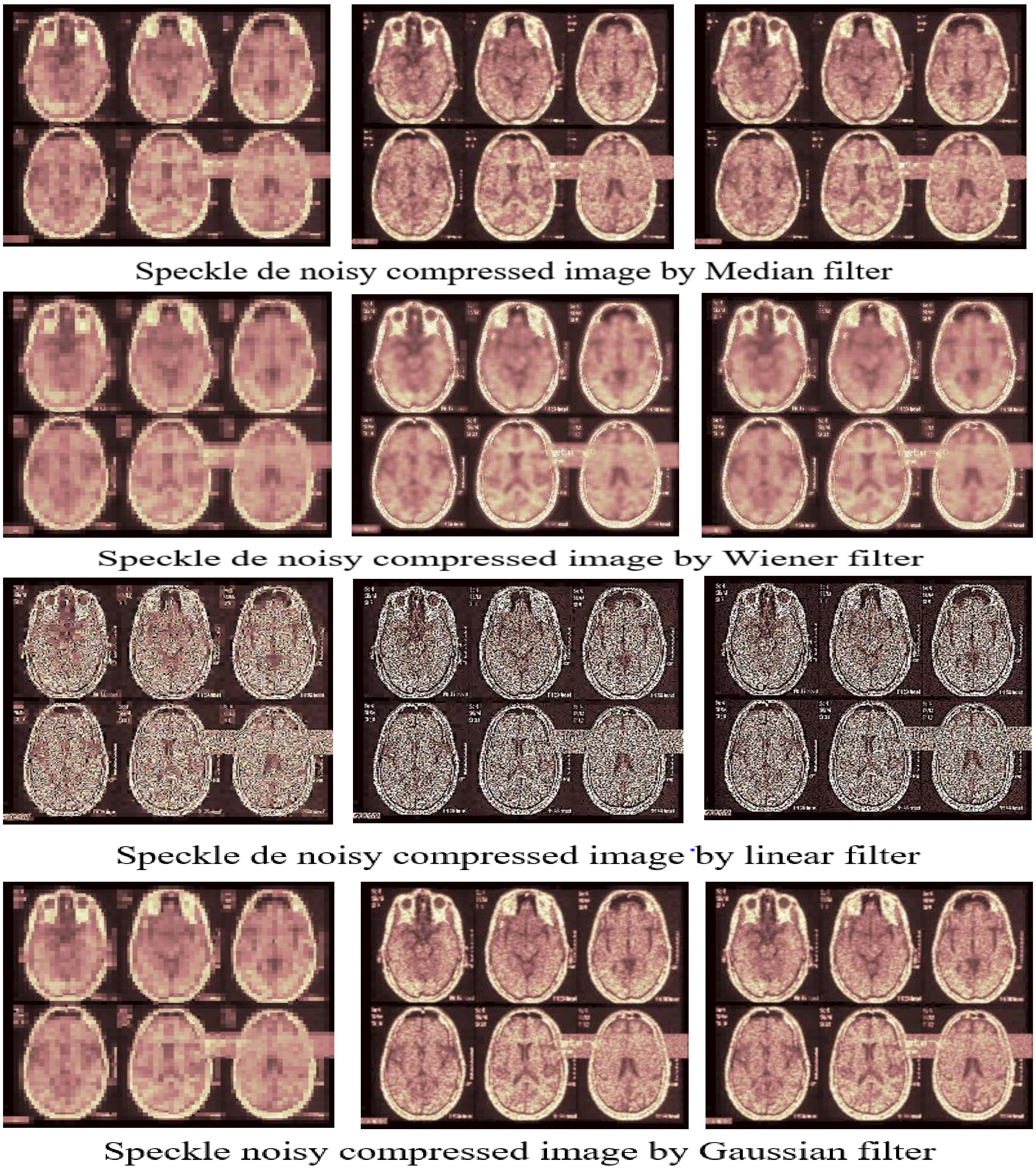


Figure 5.2.2 (d): Speckle de-noised compressed image by differnt filter

Now the de-noised image has been compressed and the size in different method is given below in a tabular form.

Table 5.2.2: De-noised compressed images size in different filter

Thresholding method	Salt & pepper de-noised				Gaussian de noisy				Sinusoidal de noisy				Speckle de noisy			
	Median Filter	Wiener Filter	Linear Filter	Gau. Filter	Median Filter	Wiener Filter	Linear Filter	Gau. Filter	Median Filter	Wiener Filter	Linear Filter	Gau. Filter	Median Filter	Wiener Filter	Linear Filter	Gau. Filter
Balance sparsity-norm	12.9 KB	13.8 KB	23.8 KB	14.6 KB	13.9 KB	12.8 KB	31.5 KB	13.9 KB	16.3 KB	15.3 KB	25.0 KB	16.5 KB	13.3 KB	12.7 KB	28.7 KB	13.4 KB
Remove near-zero	15.8 KB	17.4 KB	31.4 KB	18.4 KB	20.3 KB	16.5 KB	37.7 KB	19.8 KB	18.4 KB	16.8 KB	30.6 KB	17.8 KB	17.3 KB	16.4 KB	32.5 KB	17.5 KB
Bal. sparsity norm(sqrt)	15.6 KB	17.1 KB	31.2 KB	18.4 KB	18.9 KB	15.9 KB	38.9 KB	18.9 KB	18.9 KB	17.3 KB	30.5 KB	18.3 KB	17.1 KB	16.2 KB	34.2 KB	17.3 KB

CHAPTER 6

CONCLUSION

The Wavelet Transform tool has been considered to analysis the images to get proper investigation in the project. Wavelet can detect the small change of abnormalities so the small variance has been compared. The image size is compressed and the compression ratio is found as like the existing method. Different threshold method gives different compression ratio because the threshold value is closely related to the compressed image. By increasing and decreasing the value of the different variance has been appeared. On the other hand, the amount of effectiveness to the noises causing abnormalities in an image is also observed in the statistical table. The performances of filter in the affected noise have also been talked about briefly with existing analysis. The de-noised images have been compressed and the size of de-noised compressed image is represented by a tabular form at the last.

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APPENDIX

MATLLAB CODE:

```
clc;
close all;
% read the text image
 mygrayimg = imread ('brainmri.jpg');
 gmygrayimg = imresize (mygrayimg,[256 256],'nearest');
 In=rgb2gray(gmygrayimg);% use if the image containing RGB value 3
%  subplot(2,3,1);
figure
 imshow(In);
 title(' original image in grayscale');
%  add salt and peper noise  with noise density 0.02
 salt = imnoise ( In,'salt & pepper',0.02);
%  subplot(2,3,2);
figure
 imshow(salt);
 title(' salt & pepper noisy image');
%  use median filter in salt and pepper
 Kmedian = medfilt2(salt);
 figure
imshow(Kmedian)
title(' used median filter in salt & pepper');
%  use wiener filter in salt and pepper
sawiener = wiener2(salt,[5 5]);
figure
imshow(sawiener)
title('used wiener filter in salt & pepper');
% use linear filter in  salt and pepper
safilter = fspecial('unsharp');
saimfilter = imfilter(salt,safilter);
figure
imshow(saimfilter)
title('used linear filter in salt & papper');
% use gaussian filter in salt and pepper
sal = fspecial('gaussian',2, 5);
sfilter = imfilter(salt, sal);
figure
imshow(sfilter)
title('used gaussian filter in salt & pepper')
%  add gaussian noise with mean 0 and variance 0.01
 gau = imnoise ( In, 'gaussian', 0,0.01);
%  subplot(2,3,3);
figure
```

```
 imshow(gau);
 title(' gaussian noisy image');
%  use median filter in  gaussian
 Gmedian = medfilt2(gau);
 figure
imshowpair(gau,Gmedian,'montage')
title(' used median filter in gau');

% use wiener filter in gaussian
Kwiener = wiener2(gau,[5 5]);
figure
imshow(Kwiener)
title(' used wiener filter in gau');
% use linear filter in gaussian
gfilter = fspecial('unsharp');
gimfilter = imfilter(gau,gfilter);
figure
imshow(gimfilter)
title('used linear filter in gau');
% use gaussian filter in gaussian
H = fspecial('gaussian',2, 5);
I = imfilter(gau, H);
figure
imshow(I)
title('used gaussian filter in gau')
%  add sinusoidal noise
 [x,y] = meshgrid(1:256,1:256);
 mysinusoidalnoise =15*sin(2*pi/14*x+2*pi/14*y);
 noiseim3= imresize (mysinusoidalnoise,[256,256 ],'nearest');
 mynoiseimg1 = double(In)+noiseim3;
 noiseim2 = imresize (mynoiseimg1,[256,256 ],'nearest');
%  subplot(2,3,6);
figure
 imshow(noiseim2,[]);
 title ('sinusoidal noisy image');
%  use median filter in sinusoidal noisy image
 smedian = medfilt2(noiseim2);
 figure
imshowpair(noiseim2,smedian,'montage')
title('used median filter in sinu noise');
% use wiener filter in sinusoidal noisy image
swiener = wiener2(noiseim2,[5 5]);
figure
imshow(swiener)
title('used wiener filter in sinusoidal');
% use linear filter in sinusoidal noisy image
```

```
fil = fspecial('unsharp');
limfilter = imfilter(noiseim2,fil);
figure
imshow(limfilter)
title('used linear filter in sinusoidal');
% use gaussian filter in sinussiadal
sinu = fspecial('gaussian',2, 5);
sifilter = imfilter(noiseim2, sinu);
figure
imshow(sifilter)
title('used gaussian filter in sinusoidal');
% speckle noise add with 0.09
specklen = imnoise ( In,'speckle',0.09);
figure
 imshow(specklen);
 title('speckle noisy image');
%  use median filter in  speckle noisy image
 spmedian = medfilt2(specklen);
 figure
imshow(spmedian)
title('used median filter in speckle noisy image');
% use wiener filter in speckle noisy image
spwiener = wiener2(specklen,[5 5]);
figure
imshow(spwiener)
title('used wiener filter in speckle noisy image');
% use linear filter in speckle noisy image
filter = fspecial('unsharp');
simfilter = imfilter(specklen,filter);
figure
imshow(simfilter)
title('used linear filter in speckle noisy image');
% use gaussian filter in speckle noisy image
spec = fspecial('gaussian',2, 5);
spfilter = imfilter(specklen, spec);
figure
imshow(spfilter)
title('used gaussian filter in speckle noisy image');
```