IMAGE RECONSTRUCTION AND REFINEMENT

Project report submitted in partial fulfilment of the requirement for the

degree of Bachelor of Technology

in

Computer Science and Engineering/Information Technology

By

Nikhil Thakur (191216)
Aryan Koundal (191203)

Under the supervision of
Dr. Himanshu Jindal, Assistant Professor (SG)

To

Department of Computer Science & Engineering and Information Technology

Jaypee University of Information Technology Waknaghat, Solan-173234, Himachal Pradesh

Certificate

Candidate's Declaration

I hereby declare that the work presented in this report entitled "**Image Reconstruction and refinement**" in partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering/Information Technology** submitted in the department of Computer Science & Engineering and Information Technology, Jaypee University of Information Technology Waknaghat is an authentic record of my own work carried out over a period from August 2022 to December 2022 under the supervision of Dr Himanshu Jindal, Assistant Professor (SG), Department of Computer Science and Engineering.

I also authenticate that I have carried out the above mentioned project work under the proficiency stream ...Cloud...Computing.......................................

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

Nikhil Thakur 191216 Nikhil.
Aryan Koundal 191203 Aryan.

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

Himanshu Jindal

Dr. Himanshu Jindal
Assistant Professor (SG)
Department of Computer Science and Engineering
Dated: ~~17th November, 2022~~ 01 May, 2023

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Contact No. 9459159628/8091727724 E-mail. 191203@juitsolan.in, 191216@juitsolan.in
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Aryan Koundal 191203

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No.	Abbreviation	Full Form
1.	RGB	Red green blue
2.	PSNR	peak signal-to-noise ratio

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ABSTRACT

Image reconstruction has been expanded dramatically over the last few years. As the field of image processing increases vastly in different fields for different uses. The use of different techniques in it also increases like; image compression, image enhancement, image segmentation, image manipulation, image generation and image reconstruction for using the same image data for different purposes. The implementation of image processing by different techniques makes it more and more effective and easy to use with proper knowledge. Image reconstruction is one of the image processing techniques used to regain or recreate any image. Image reconstruction is done for image processing to reconstruct images that contain noise or any other factor that degrades an image. There are different types of noises like: gaussian noise, poisson noise, s&p noise, speckle noise etc. This image noise can be caused by various physical and environmental effects. The image reconstruction techniques mainly regain the features of the image that are lost by any factor that affects an image. In this paper, we used wavelet transform denoising techniques and denoising filters to reconstruct the images for eliminating noise.

CHAPTER-1: INTRODUCTION

1.1 Introduction

The technique of recovering the image into its previous state of clear image from damaged ones is known as image reconstruction. Motion blur, poor resolution, and noise, the main focus of our paper are some of the corruptions. An accurate portrayal of a genuine picture with colour and brightness variations is image noise. Image noise is mostly caused by a simple process in which image’s quality is degraded when photons arrive on its surface, which causes dirty grains on images with unpredictable intensities. In some circumstances, this technique significantly lowers visual pleasure and image details like edges. Due to cost and space considerations, mobile phones often come with lower-quality camera lenses and sensors. When taking shots in the dark, the results are often noisy and cluttered. The requirement for an effective noise-removing algorithm has increased due to the increased use of mobile devices. The noise might be further classified depending on the model we’ll use. Noise characteristics can be approximated by utilising the Gaussian distribution. The noise that is studied and categorised the most is gaussian noise. The number of independently arriving photons is taken into account by the Poisson noise model. Because the photons arrive at a constant rate and independently of one another, we can assume that they are sampling from a distribution. The scenes at night, medical scans, and images produced in astronomy are some famous instances of less-light and limited-photo circumstances. These noises were not extensively studied because of their rarity. As smartphone use increases, more and more night images are being taken. The main approaches we used to reconstruct the images are different types of wavelet denoising techniques and denoising filters. All wavelet denoising techniques work with the same thresholding part as a medium for reconstruction of images but only the methods differ. We used all the wavelet denoising techniques and denoising filters on the same dataset for image reconstruction so we can compare the results more efficiently and effectively. For comparison, we employed wavelet transform methods and filters to reconstruct images with various PSNR values that were determined in relation to various thresholds at various sigma values. This paper mainly focuses on applying various denoising techniques and denoising filters to remove noise from images and comparing the results produced.

This paper’s major contribution can be summarised as:

1.) In wavelet denoising technique the main connection is in between thresholding value and its different methods. They let different values of standard deviation vary according to users' needs. The quality of images reproduced in this are good.

2.) The denoising filters use different thresholds for denoising different types of noises from images using filters according to the user's need.

1.2 Problem Statement

Reconstructing the same image by removing various aspects like noise and processing differences is the essential step in reusing any image that has been contaminated. The images are a significant component because they convey more meaningful information than any other feature. A number of things, especially noise, low resolution, and mild blur, affect how an image looks. An image can be used to reproduce its appearance by removing specific components from the original image and recreating it. But in some cases, it would also be feasible to consider digitally rebuilding a physical photograph whose appearance has been changed by ageing or environmental variables. Thus, the useful information in images or photographs must be preserved by any means, which is affected by different factors and degradations.

1.3 Objectives

The goal for reconstructing images is to "compensate for" or "undo" imperfections that reduce any image's characteristics and quality. This containment appears in a number of ways, such as blur in motion, difficulties in the focus by cameras, and numerous noises have an immediate effect on our image. Any image's original score reveals the true content and is much more appealing than one with several degradations, such as noise and other image-affecting flaws, which renders the image unclean or asymmetrical. If we broaden this idea to include reconstruction, it is not just restricted to digital images but photographs also possess a significant role in this idea as well. The quality of the photos deteriorates with time owing to ageing and a variety of other factors. For example, even when left untouched, the photos tend to become blurry over time and are affected by various noises. Even when an image is kept in a safe location and is safeguarded in various ways, its quality abruptly deteriorates with time as it becomes older. the process of reconstructing images using various wavelet transform techniques, each of which produces a different set of results when applied to the same dataset. The key objective of image reconstruction is to repair damaged images using the wavelet transform. The other method we have used to rebuild images is denoising filters. With filters, images with different types of noises can be reconstructed. In reconstruction by wavelets we used a number of thresholding techniques such as visushrink, bayesshrink and sure shrink for reconstruction and concluded the best for reconstructing images. In filter denoising reconstruction we used different filters for reconstructing images and concluded the one best for reconstructing images by calculating the best image quality. This work focuses on the reconstruction of noise-damaged images that can then be recovered and used again.

1.4 Methodology

1. Wavelet Transform

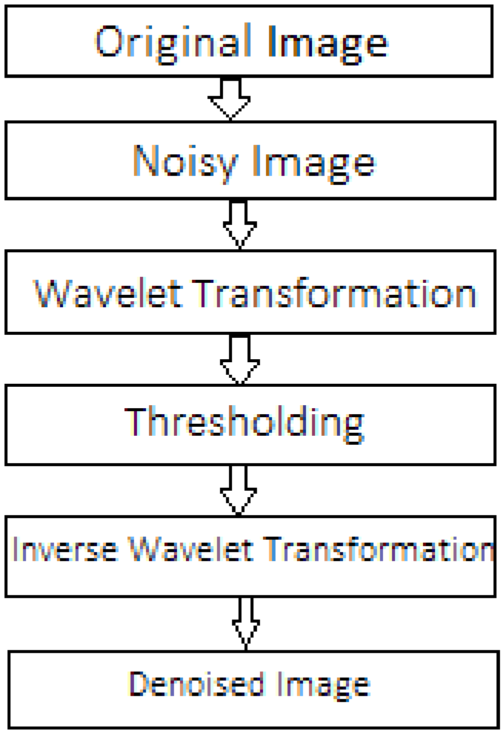


Fig:1 - Flow chart of Wavelet Transform

In Wavelet Transform the first step is collection of image data. The image data is further contaminated with noise, and wavelet transform is then applied to the data using the user's desired thresholds. Finally, an IWT is used to obtain the denoised image which is reconstructed.

2. Filter Denoising

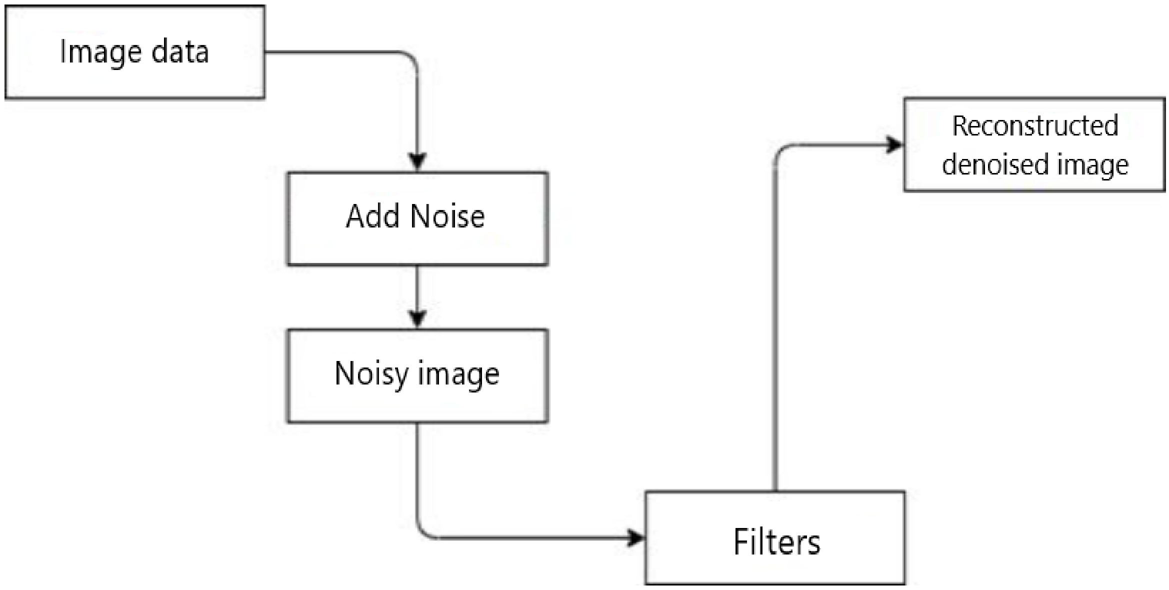


Fig:2 - Flow chart of Filters

In Filter denoising the first step is collection of image data. The image data is further contaminated with noise by different values of standard deviation and the desired filter is then applied to the noisy image data using the user's desired thresholds. Finally, the denoised image is obtained after reconstructing the image.

1.5 Organization

Chapter 1: Introduction

This section covers a variety of topics related to the project, including a simple introduction, methodology, description of the problem, and information of the project's goal.

Chapter 2: Literature Survey

The literature survey of this project discusses the material reviewed and the concepts that have been researched and acknowledged.

Chapter 3: System Development

The system development covers project's analysis and how the specific system design of the work done is implemented, are discussed in this section. Along with the project snapshots, it also discusses the algorithms employed in this project.

Chapter 4: Performance Analysis

By displaying the outcomes using snapshots and comparing them to one another, this section of the project demonstrates the performance analysis of the project. In this section, several outputs are also displayed.

Chapter 5: Conclusion & Future work

This section of the project finished the work on the project we were given and shows the work that can be carried out further on it in the future.

CHAPTER-2: LITERATURE SURVEY

2.1 Literature review

Before delving into the specifics of the literature we reviewed, a lot of academic researchers and different paper author's have proposed different current materials of research on reconstructing images that employ a variety of methods, various filters, different transforms , a combination of transform domain and spatial domain techniques, etc.
The research on various approaches carried out by various researchers that is relevant to our topic is briefly summarised below.

Yungang Zhang et al.[1] has suggested comparing thresholding techniques for wavelet-based picture reconstruction. Reconstruction of a picture using wavelets is a significant technique for minimising image noise. Wavelets' intrinsic capacity to represent images in a very sparse way serves as the basis for wavelet-based denoising through thresholding. The wavelets denoising thresholding techniques explored in this study include Visushrink, SureShrink, BayesShrink, and Feature Adaptive Shrinkage. Additionally, the PSNR-based quantitative assessment of these techniques is provided.

B.K. Shreyamshaa Kumar et al.[2] has presented a gaussian/bilateral filter-based picture denoising and associated noise thresholding approach. In addition to taking into account the geometric proximity of adjoining pixels and their similarity in terms of grey levels, the bilateral filter, which is also local but non-linear, also smooths the edges. The edges and features of the image are completely blurred by the local and linear Gaussian filter. The dual filter's multi-resolution variant is applied to a decomposed image's approximate subbands, as well as following each wavelet reconstruction level. Some visual features are lost when the approximation subband is filtered bilaterally, but the image takes on a remarkable aspect at each level, wavelet reconstruction is used. It is advised to combine a bilateral/gaussian filter for addressing all the problems. The benefits of the offered approaches is that they compute more quickly.

Mukund N Naragund et al.[3] has proposed a wiener filter and thresholding technique efficient in image reconstruction. The Wiener filter used a linear stochastic framework to demask the images. This study proposes a method for improving the performance of a filter used to eliminate noise in an input image. The filter aims to reduce the mean square error between the intended and estimated image but has a disadvantage of performing poorly with unpredictable and random noise. The proposed technique combines NeighSure shrink thresholding with a Wiener filter based on wavelets. The method includes noise thresholding and outperforms other techniques such as wavelet thresholding, Wiener filtering, and Gaussian filtering in terms of visual quality, Peak Signal to Noise Ratio, and Image Quality Index.

B Naga Venkata et al.[4] has suggested comparing different thresholding techniques for denoising images. Wavelet-based denoising is a method that aims to maintain the characteristics of the signal while reducing noise, irrespective of its frequency content. It involves a nonlinear thresholding step and a linear inverse wavelet transform, or a linear forward wavelet transform. Wavelet shrinkage, a non-linear procedure, is utilised to set itself apart from complete linear denoising. Wavelet shrinkage depends on the choice of a thresholding parameter and the method used to calculate the threshold. Various strategies can be used to choose denoising parameters, but there isn't yet a "best" method for determining the threshold globally. In order to find the optimum method for picture denoising and reconstruction, numerous denoising approaches, including Sure Shrink, Bayes Shrink, and Visu Shrink, are applied.

Sudipta Roy et al.[5] has proposed a new hybrid image denoising method. In this paper, a novel model for denoising of various noisy pictures based on wavelet and bilateral filter hybridization is proposed. Standard pictures such as x-ray, ultrasound, and astronomical telescopic images are used to test the model, and its performance is assessed in terms of peak signal to noise ratio (PSNR) and image quality index (IQI). The results show that the performance is worsened when bilateral filters are used on subbands of a decomposed image along with wavelet thresholding filters. However, the performance is improved by using bilateral filters both before and after decomposition. Between the four models taken into consideration in this study, the filter produced with bilateral filters before and after the decomposition of an image is found to have the best performance in terms of PSNR and IQI. Additionally, the suggested filter produces outcomes that are essentially consistent and homogeneous across all images.

Swetha Danda et al.[6] has proposed a comparison of the bilateral filter and tv-norm minimization for image denoising. In this study, the bilateral filter (BF) and total variation norm (TV-Norm) reduction were put side by side. By combining non-linear domain and range filters, the bilateral filter maintains edges while reducing noise. The TV-Norm reduction approach reduces the input image's overall fluctuation within certain bounds. They measured the performance of the two filters using Mean squared error estimates and L1-norm. They apply TV-Norm reduction and bilateral filters with various spatial windows to 2D brain pictures with various noise levels. It is noticed how the parameters and the spatial window size affect the bilateral filter's performance and how well these two filters preserve edges.

Alisha P B et al.[7] has proposed image denoising techniques. The act of removing different types of noise from the images is a critical step in image processing. The majority of an image's noise sources happen during the image's acquisition, transmission, and storage. Image denoising is a common difficulty in a variety of image processing and computer vision issues. There are numerous technologies now in use to denoise photos.The crucial characteristic of a successful picture denoising model is that it should entirely eliminate noise while maintaining edges. The method of image denoising will primarily depend on the kind of image and how noise interacts with it. There are numerous published algorithms, and each one has its own presumptions, benefits, and drawbacks. The review of certain noise models and substantial contributions to the field of picture denoising are concluded in this study.

Shamaila Khan et al.[8] has suggested using several shrinkage approaches and basic noise to denoise photos using varying wavelet thresholding. High levels of signal scarcity can be described using wavelet transforms. The signal estimating method known as wavelet thresholding uses the signal denoising capabilities of the wavelet transform. To choose the most effective thresholding approach for photo denoising, it will compare a number of thresholding approaches including Visu Shrink, Bayes Shrink, and Sure Shrink. To obtain better PSNR data, the threshold value must be changed.

M.Neelima et al.[9] has suggested thresholding techniques by using wavelet transform for image denoising. The work in this paper says, they might represent extremely rare signals. This is the fundamental notion behind the non-linear wavelet-based signal estimation technique known as wavelet denoising. The wavelet technique by thresholding, which assesses signals, makes use of the properties of the wavelet transform for signal denoising. The goal of this study was to compare multiple methods for image denoising and choose the most effective one. These methods were visushrink, sureshrink, and neighbour shrink. In this work, we suggest a better method for determining the ideal threshold and neighbouring window size for each subband by using Stein's unbiased risk assessment.

J.-B. Wang et al.[10] has proposed an improved method for image denoising based on fractional-order integration. A new method based on fractional integration is suggested because the present picture denoising techniques distort an image's texture features. A numerical method is used to determine the approximate value of the fractional-order integral operator after first deducing the fractional-order integral formula by generalising the Cauchy integral. Finally, in the image's eight pixel directions, a fractional-order integral mask operator of any order is built. The suggested image denoising approach may preserve the image's edge texture information while reducing noise, according to simulation findings. Because a texture protection mechanism is used throughout the iterative processing, this method can also achieve greater image feature values and better picture vision than the previous denoising methods.

J. Liu et al.[11] has proposed image denoising searching similar blocks along edge directions. The performance of the block-matching and 3D filtering (BM3D) method may be constrained when handling edges because it uses predefined directions to look for similar blocks over the entire image. In this study, we suggest a method for finding candidate matching blocks along edge directions that are ideally suited to picture details. A 3D group made of all related blocks by reducing the 3D transform coefficients that were applied to these groups, denoising is accomplished. The experimental results demonstrate that the suggested method surpasses some of the existing denoising methods in terms of numerical results and visual quality. In addition, the proposed method adds few artefacts while maintaining edges and textures.

A. Hadj Fred et al.[12] has proposed GPU-based anisotropic diffusion algorithm for video image denoising. The Oriented Speckle Reducing Anisotropic Diffusion (OSRAD) filter is an anisotropic diffusion technique that is presented in this study. The OSRAD is particularly effective at de-speckleizing photos. However, due to its powerful computational cost, this filter cannot be used in real time. Through the optimisation of the graphics processor unit, the study's goal is to reduce the processing time required to apply the OSRAD filter utilising a parallel processor. The outcomes demonstrate how well the suggested method performs real-time video processing. With this configuration, 128 128 pixels can be denoised at a rate of 25 frames per second. Compared to the typical central processing unit (CPU) implementation, the proposed model accelerates image filtering by 30 times. The mean structural similarity index, peak signal-to-noise ratio, and figure of merit are a few examples of metrics that provide a quantitative comparative measure. When compared to the bilateral filter and the wavelet transformation, the modified filter is faster than the traditional OSRAD and maintains a good level of image quality.

Sutha et al.[13] has proposed denoising natural images using fast multiscale directional filter banks. In order to identify the appropriate subband for the estimation of the noise reduction threshold value, this algorithm employs a subband selection technique. Any denoising algorithm's effectiveness is mostly dependent on fixing the ideal threshold. Because of its directionality and low computational cost, Fast Multiscale Directional Filter Bank (FMDFB) is an ideal reconstruction framework suitable for many image processing applications. In contrast to wavelet subbands, each subband in FMDFB contains substantial information about the image's content. Therefore, a straightforward subband adaptive shrinking approach based on wavelets has a tendency to over smooth the FMDFB coefficients. To solve this problem, the suggested algorithm chooses the appropriate subband based on the statistical characteristics of the subbands for the estimation of the threshold value.

Peng LIU et al.[14] has proposed a new Image Denoising Algorithm via Bivariate Shrinkage Based on Quaternion Wavelet Transform by removing blemished photos caused by additive white. A common issue in image processing is gaussian noise. Using quaternion wavelet transform and bivariate shrinkage function, the algorithm for removing Gaussian noise from distorted images is proposed in this study. To extract the quaternion coefficients for each sub-band, the image is decomposed using a quaternion wavelet transform. Then, the statistical dependencies between the intra-scale quaternion coefficients are modelled using a bivariate shrinkage function filter utilising the maximum a posteriori. In terms of PSNR, the suggested algorithm is contrasted with different denoising methods. The experimental findings show that the suggested approach works noticeably better than the other denoising strategies.

B. Yang et al.[15] has proposed Image Compression Based on Compressive Sensing Using Wavelet Lifting Scheme. This study provides a brand-new technique for compressive sensing

(CS)-based picture compression that makes use of CDF9/7 wavelet transform's sparse basis. The input image's three layers of wavelet transform coefficients are subjected to the measurement matrix in order to perform compressive sampling. Three alternative measurement matrices, including the Gaussian, Bernoulli, and random orthogonal matrices, were used. Each level of the wavelet transform is separately rebuilt using the orthogonal matching pursuit (OMP) and basis pursuit (BP) methods. According to experimental findings, the suggested method produced compressed images of higher quality than those produced by existing methods using different objective (PSNR/UIQI/SSIM) measurements and proposed image quality evaluation indices.

2.2 Table for Literature review

Sr. no.	Author(s)	Advantages	Disadvantages
1.	Fei Xiao, Yungang Zhang	Concurrent localization in the time and frequency domains is provided.	Not enough phase information is provided.
2.	B. K. Shreyamsha Kumar	The effectiveness of the low-pass feature can then be adjusted manually by adjusting the filter's width.	The labor-intensive filter that was employed to reconstruct the image eliminates details.
3.	Priya B S, Basavaraj Jagadale, Mukund N Naragund,Vijayalaxmi Hegde	In this, the blurring and the extra noise are concurrently reversed, and the wiener filtering performs best in terms of mean square error.	It is difficult to try to determine the power spectrum in this. It is very challenging to perform a perfect repair because of the noise's unpredictable nature and it performs worse when the noise is random and unknowable.

Sr. no.	Author(s)	Advantages	Disadvantages
4.	Shivani Mupparaju, B Naga Venkata Satya Durga Jahnavi	Due to the rapid wavelet transform, computation takes relatively little time.	The sensitivity of the wavelet transform technique cannot be changed.
5.	Sudipta Roy, Nidul Sinha, Asoke K. Sen	This hybrid model is more effective and efficient since it combines wavelet transform and bilateral filter.	Due to the combination, processing takes a long time computationally.
6.	Swetha Danda, Tim McGraw	Both filters perform well on grayscale images.	Lack of a data fidelity constraint in the bilateral filtering process, which causes different running time for bilateral and tv filters.

Sr. no.	Author(s)	Advantages	Disadvantages
7.	Alisha P B, Gnana Sheela K	Every aspect of noises in images are fully explained for denoising.	All the filters are not covered and only briefly explained.
8.	Shamaila Khan	In this, the blurring and the extra noise are simultaneously reversed in two levels, while the reconstructed images in the other two are blurry.	The filter that is used in this to reconstruct the images decreases the image's characteristics.
9.	M.Neelima, Md. Mahaboob Pasha	NeighShrink (the proposed approach) uses the neighbourhood window size and ideal threshold to keep the important data from the deleted coefficients.	By using the provided methods, reconstructed pictures show inadequate directionality.

Sr. no.	Author(s)	Advantages	Disadvantages
10.	N. He, J.-B. Wang, L.-L. Zhang, and K. Lu	In wavelet transform, computation takes relatively little time.	The relativity of the wavelet transform technique cannot be changed.
11.	J. Liu, R. Liu, Y. Wang, J. Cheen, Y. Yang and D. Ma,	This model is more effective since it combines block-matching and 3D filtering (BM3D)	Due to the combination, processing takes a longer time computationally.
12.	A. Hadj Fredj and J. Mallek	GPU-based denoising performs well on grayscale images.	Lack of a data fidelity constraint in this filtering process, which causes different running time for GPU based denoising.

Sr. no.	Author(s)	Advantages	Disadvantages
13.	Leavline, E.J.; Sutha	Due to filter banks, computation takes less time.	The directionality of the filter banks technique cannot be changed.
14.	Shan GAI, Peng LIU, Jiafeng LIU, Xianglong TANG	This Quaternion Wavelet Transform is more effective for bivariate shrinkage.	Due to the wavelets, processing takes a long time computationally for processing.
15.	J. Jin, B. Yang, K. Liang and X. Wang	Compressive Sensing performs well on both RGB and grayscale images.	Lack of a data fidelity constraint in the Wavelet Lifting Scheme, which causes slow running time.

CHAPTER-3: SYSTEM DEVELOPMENT

3.1 Dataset

1.) Wavelet transform

For reconstruction of images by wavelet transform we used the MNIST dataset, which is easily accessible online for various purposes. This data can be used for a variety of image processing tasks because it consists of a sizable number of images of the numerals 0 to 9 that are in various forms and shapes. With a total of 70000 images in various sizes and shapes, this dataset includes distinct images of data for training and diverse images of data for testing. The reconstruction of coloured images using the wavelet transform is also demonstrated with single RGB images. Using this method, images are utilised to compare various attributes at various scalings.

2.) Filters

For reconstruction of images by filters we used the MNIST dataset, which is easily accessible online for various purposes. It comprises pictures of numbers ranging from 0 to 9, all of which have unique forms and shapes. This makes a big difference when using the data for various image processing tasks. This dataset contains a total of 70000 images in various sizes and shapes, divided into 60000 images for training data and 10,000 images for testing data.

3.2 Methods

1.) Wavelet Transform

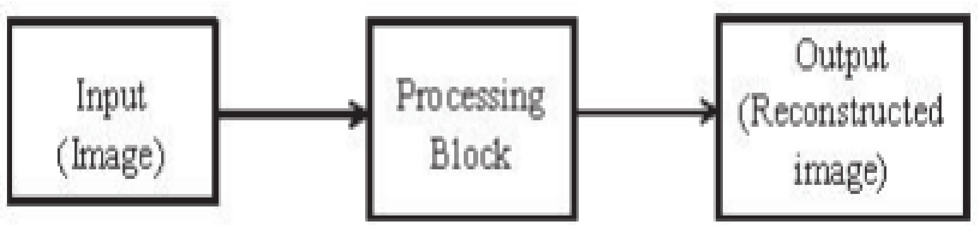


Fig:3 Implementation Block

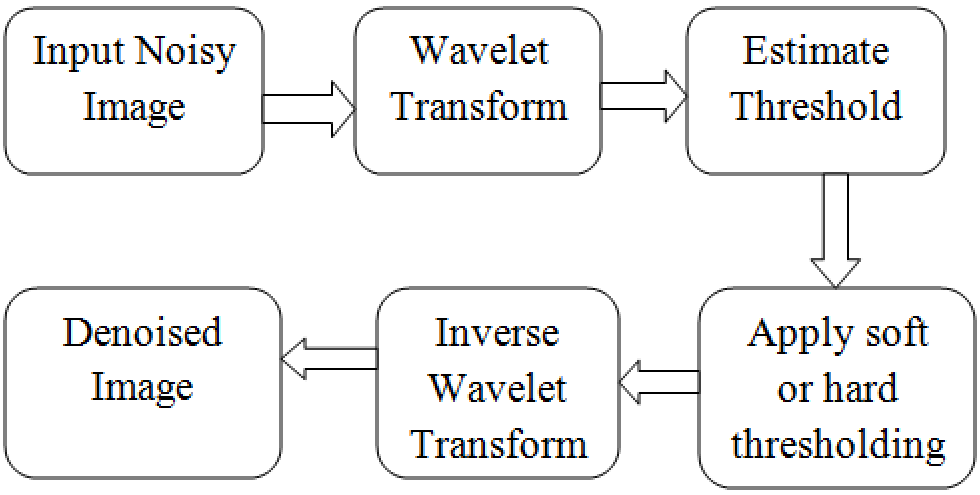


Fig:4 Processing block

The steps in processing block are follows:

Step 1: Input the image for denoising.

Step 2: Choose different types of wavelets; coiflets, haar, daubechies, biorthogonal etc. For reconstruction we have used coiflets and biorthogonal wavelets.

Step 3: Now, apply the WT(wavelet transform) to the input image w(t). New wavelet's wavelet transform can be defined as follows:

$$W(a, b)_{\alpha} = \int_{t} (w(t)\, X_{a}(v))dt$$

Step 4: In this step, for the image to be reconstructed, estimate the threshold.

Step 5: Now, using the inverse wavelet transform, the signal in the complex plane is converted into a signal in the time domain. Wavelet transform's contrary method refers to IWT.

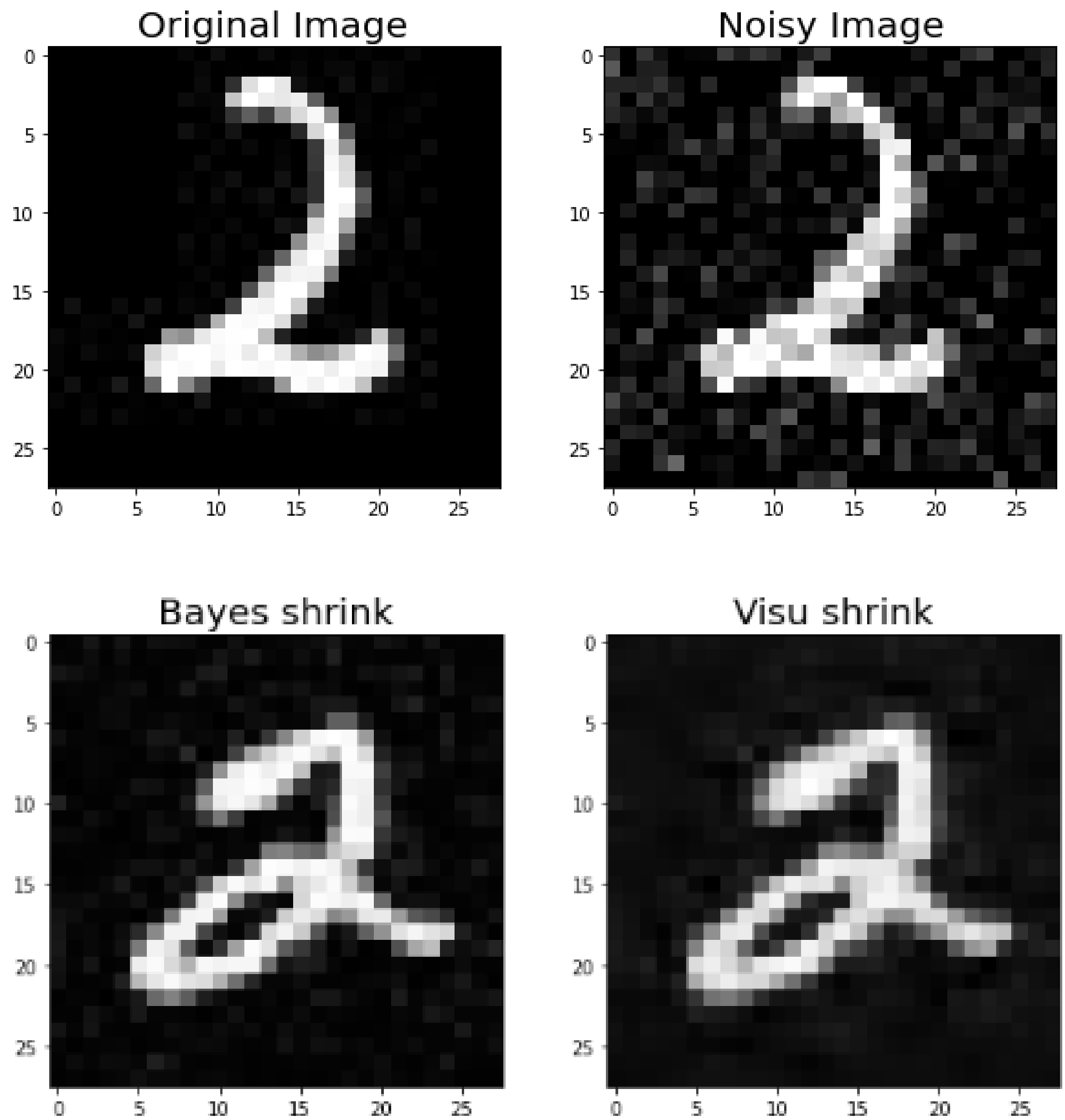
$$w(t) = \int_{a} \int_{b} (\frac{1}{a^{2}}) W\,(a, b)_{\alpha} X_{\alpha}(v)\; da\; db$$

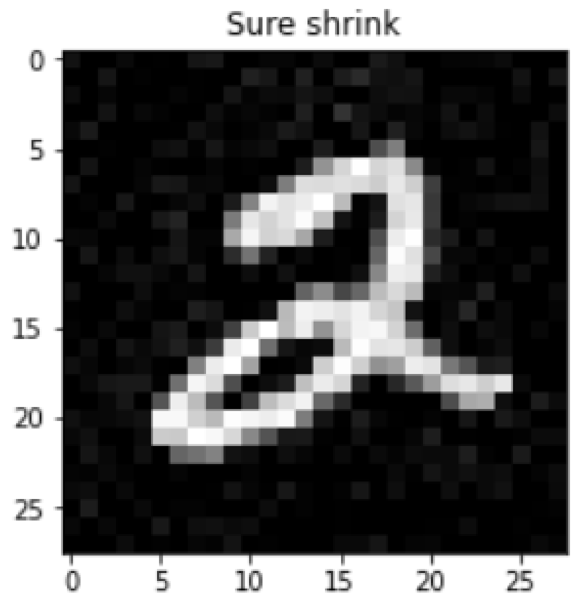
Step 6: After the IWT, the reconstructed image is created. This image's quality is further assessed by using the Peak Signal to Noise Ratio (PSNR) metrics.

Wavelet transform's results are:

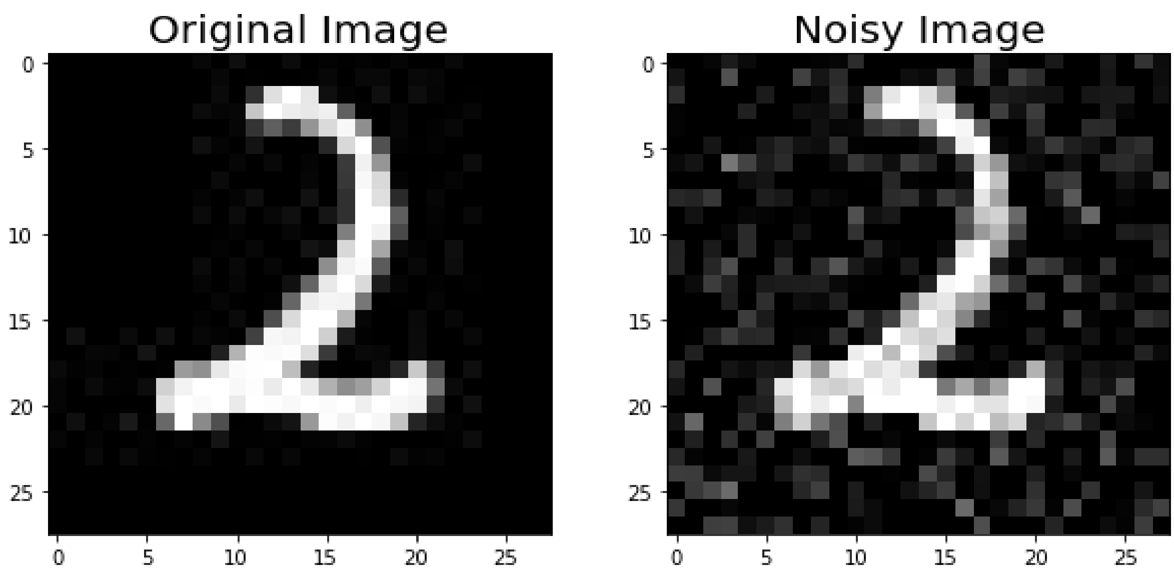
1.) Grayscale images

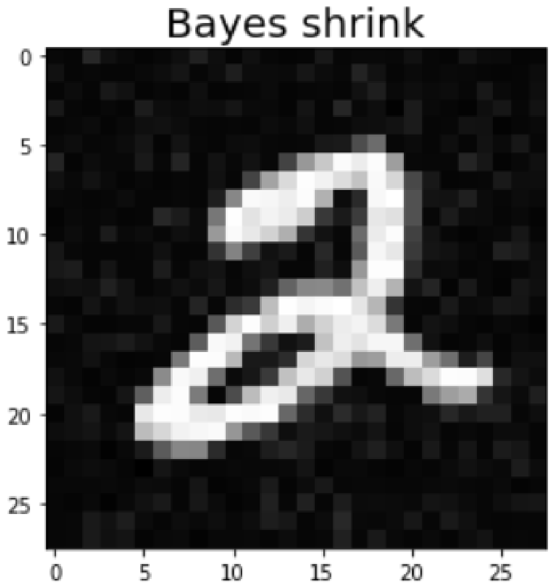
For Soft threshold:

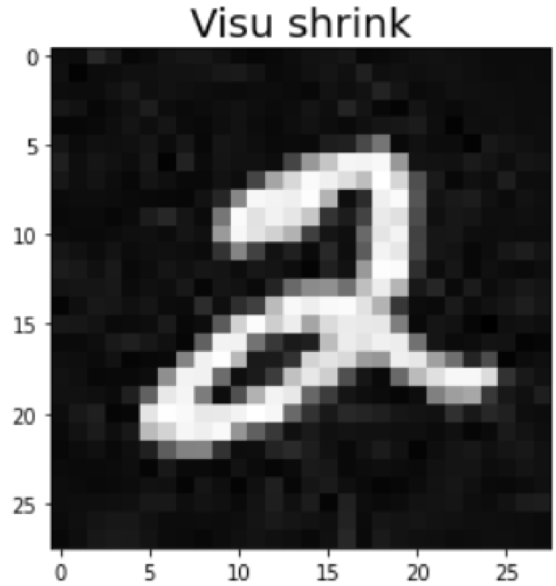


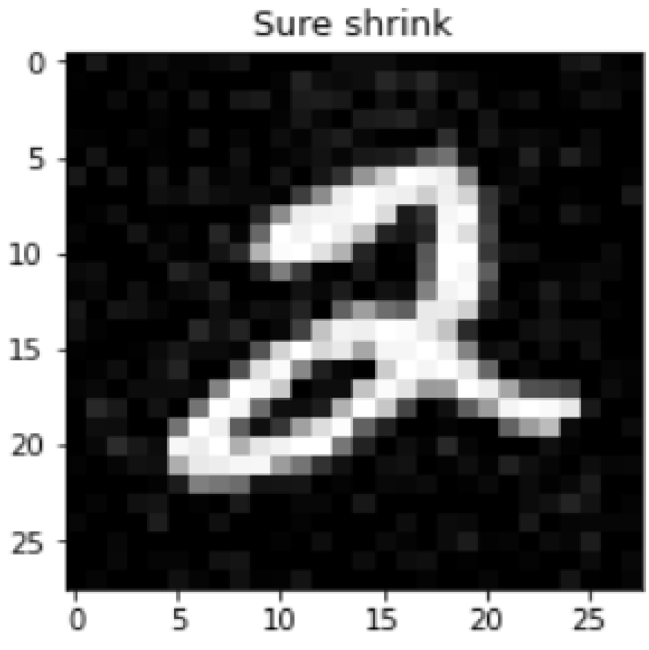


For Hard threshold:



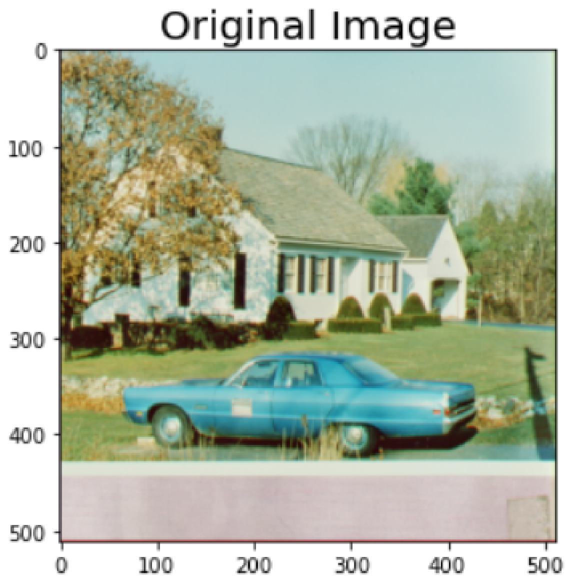

Bayes shrink

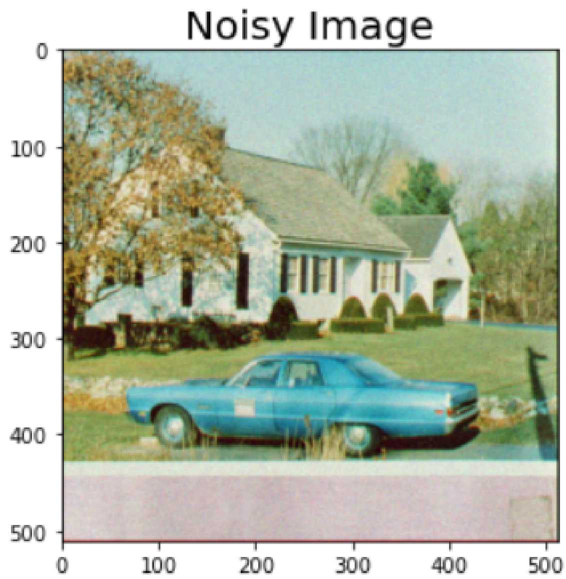

Visu shrink

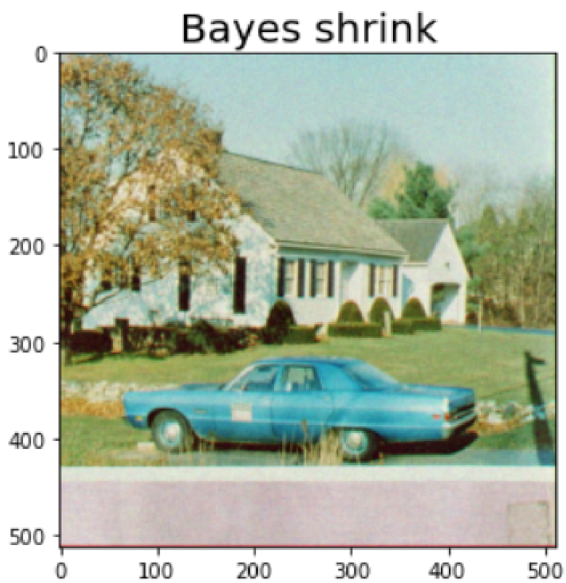

Sure shrink

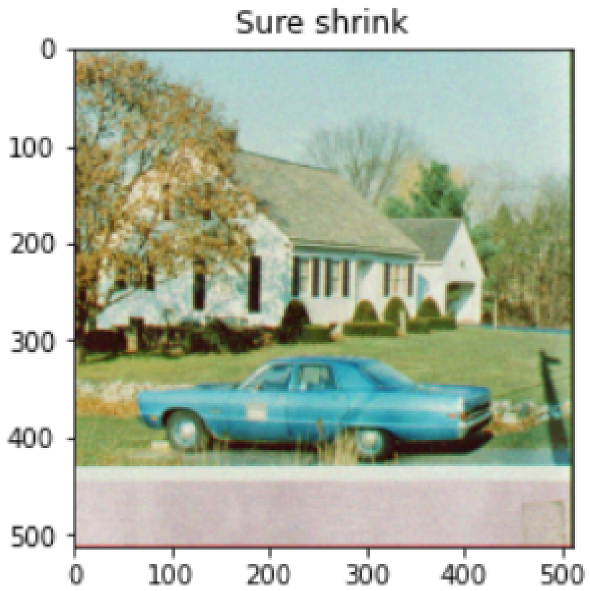
2.) RGB images

For Soft threshold:

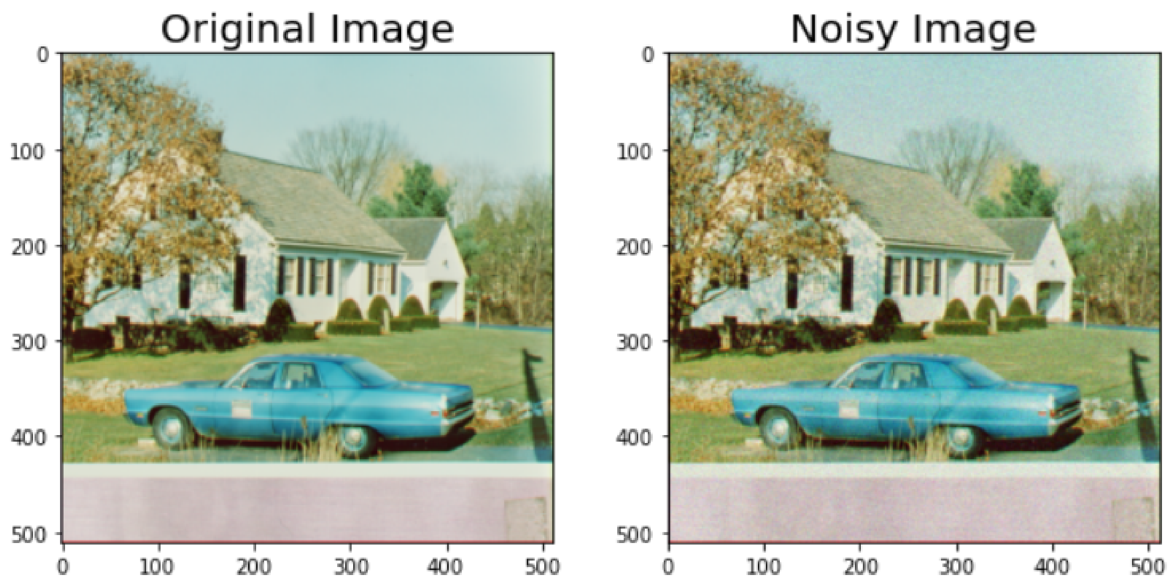


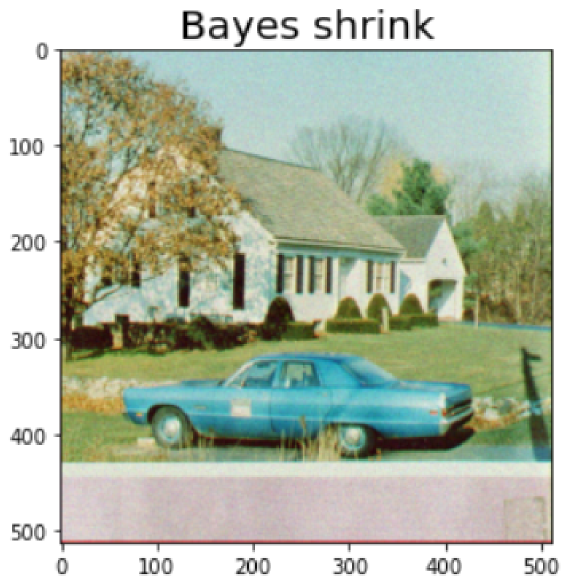


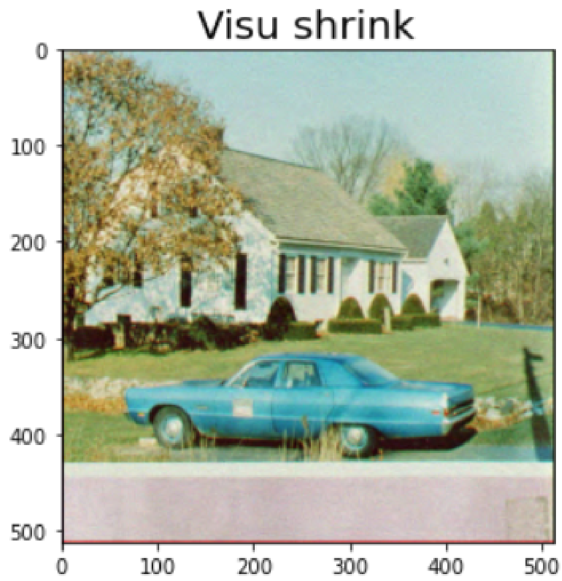


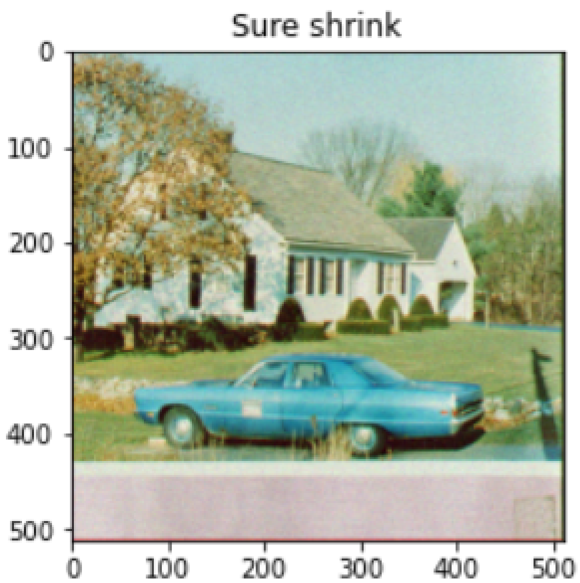


For Hard threshold:




Bayes shrink
0
100
200
300
400
500
0
100
200
300
400
500


Visu shrink
0
100
200
300
400
500
0
100
200
300
400
500


Sure shrink
0
100
200
300
400
500
0
100
200
300
400
500

2.) Filters

Different denoising filters are used for noise removal in images(grayscale or rgb) which are further categorised in different filtering techniques. In this paper, we have used and compared three non-linear filters; median filter, bilateral filter and total variation(TV) filter, for both grayscale and RGB images. These filters are used for refinement and then reconstruction of images.

2.1) Median filter

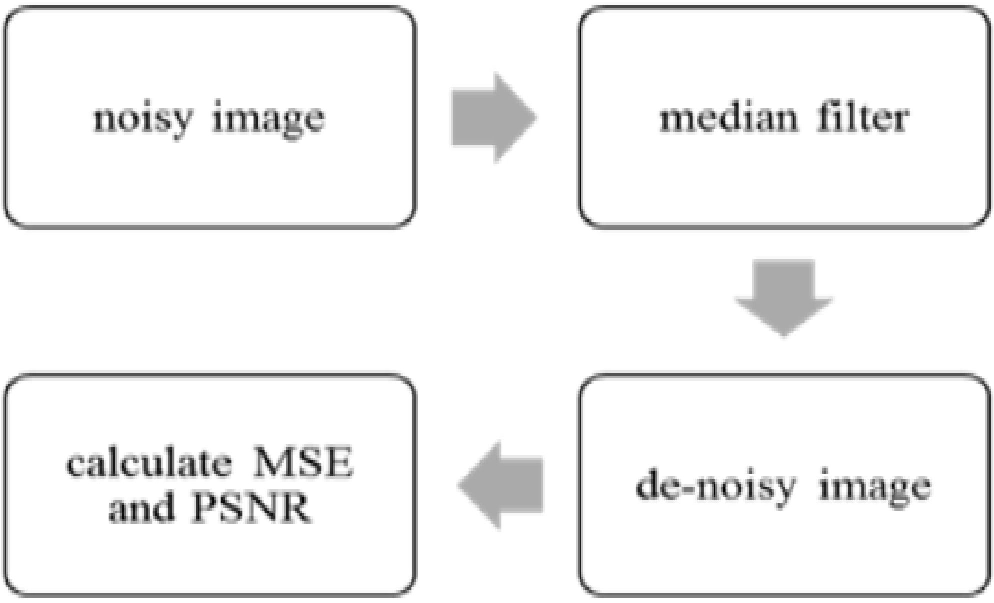


Fig. 3.3 Block diagram for implementation of Median filter

By first calculating the median value for the entire window, median filtering involves replacing each entry in the window with the median value for the corresponding pixel. The median is easy to define if the window contains an odd number of elements since it simply refers to the middle value after all the entries in the window have been sorted numerically.However, there are multiple true medians when there are an even number of entries. In image processing, median filters are employed to provide smoothness. The benefit of median filtering is that it is significantly less sensitive to outlier readings than the mean. As a result, it can eliminate these outliers without affecting the image's transparency.

Example of using a window size of three with one entry, a median filter will be applied to the following simple one-dimensional signal :

x = (5, 6, 30, 8, 5, 6)

So, the median filtered output signal y will be:

y_1 = med(5, 6, 30) = 6,

y_2 = med(6, 30, 8) = med(6, 8, 30) = 8,

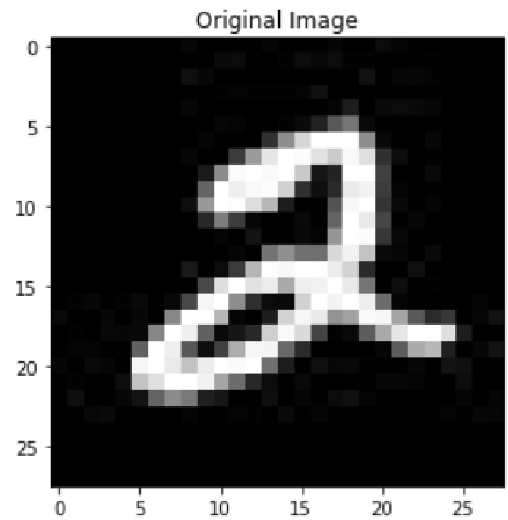
y_3 = med(30, 8, 5) = med(5, 8, 30) = 8,

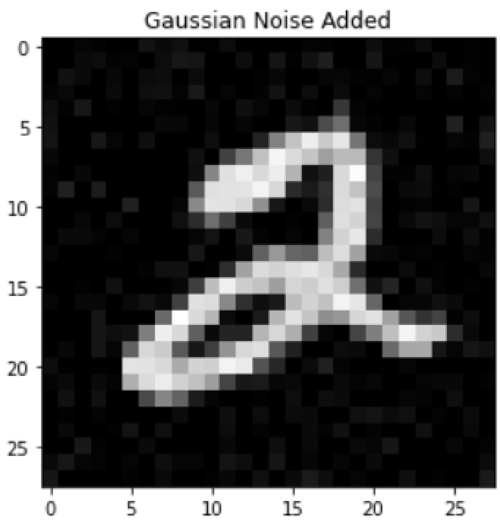
y_4 = med(8, 5, 6) = med(5, 6, 8) = 6,

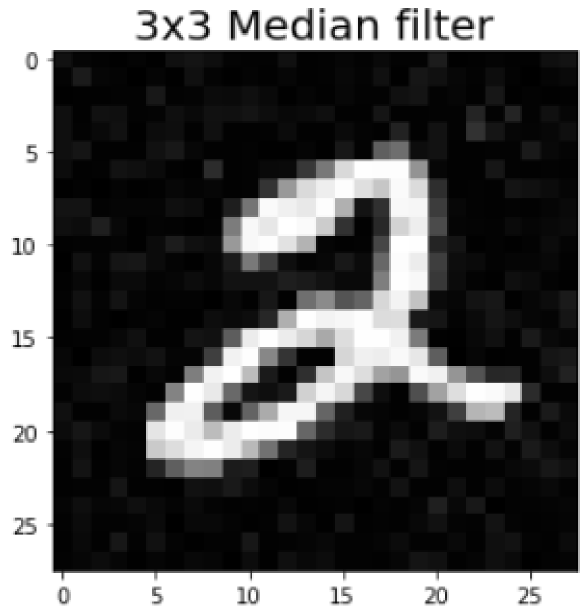
i.e. y = (6, 8, 8, 6).

Results obtained by Median filter are:

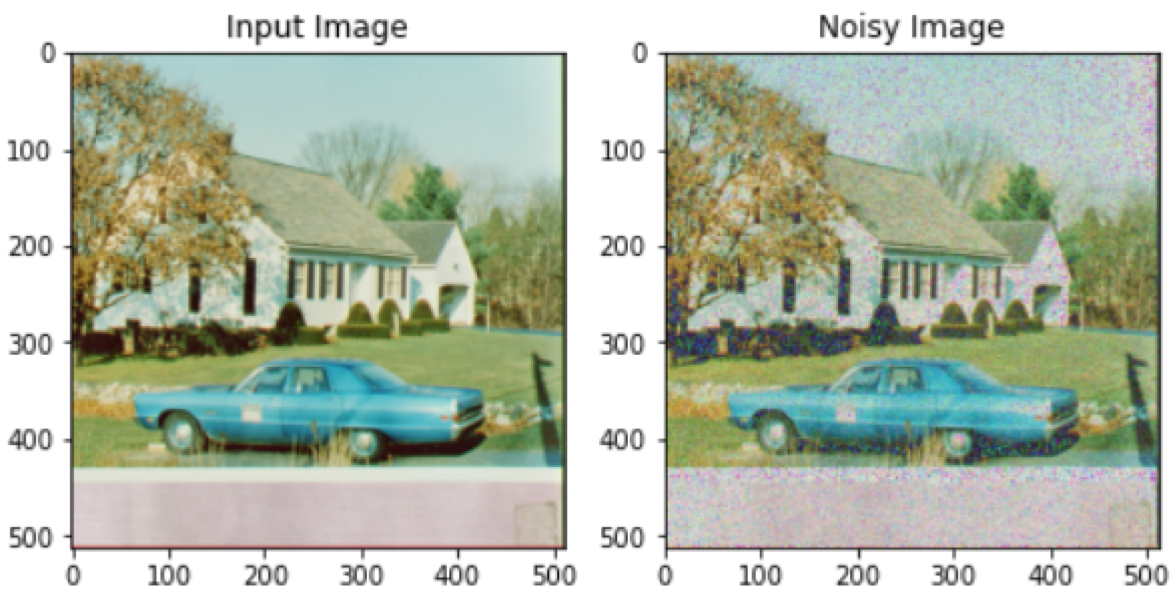
1.) For Grayscale images

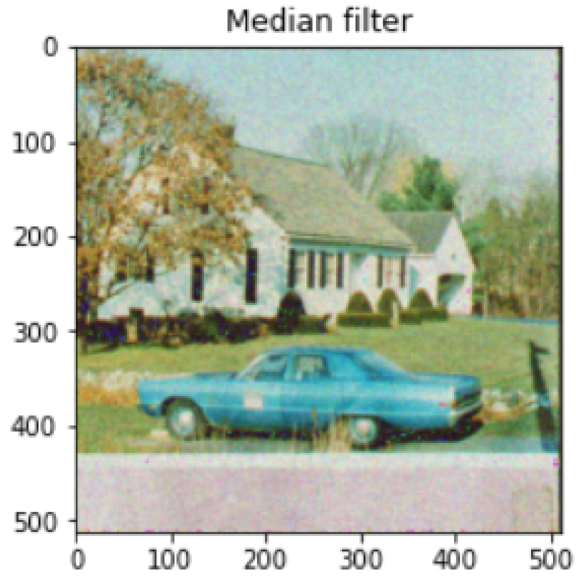






2.) For RGB images





2.2) Bilateral filter

By using a non-linear mixture of neighbouring values, a bilateral filter preserves the edges while removing noise from the images. A weighted average of the values of the adjacent and similar pixels is used to replace each pixel in the original image to create the final image. Domain and range filters can be combined to create the bilateral filter. Additionally, the weights depend on radiometric differences as well as the Euclidean distance of pixels (e.g., range differences, such as colour intensity, depth distance, etc.).

The bilateral filter is defined as :

$$I^{filtered}(x) = \frac{1}{W_P} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|),$$

Here, $I^{filtered}$ is defined as filtered image;

I is the original image which will be the input to be filtered;

x is defined as the coordinates of the current pixel to be filtered;

Ω is the window centred in x, so $x_i \in \Omega$ is said to be another pixel;

f_r is defined as the range kernel in intensities for smoothing differences;

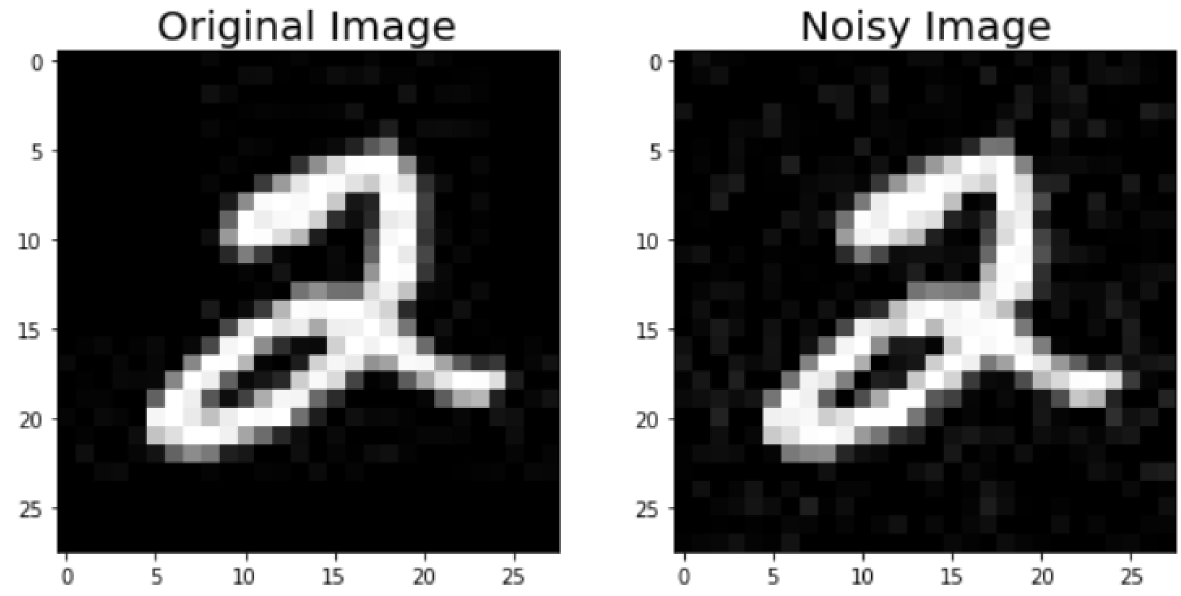
g_s is defined as the spatial (or domain) kernel in coordinates for smoothing differences;

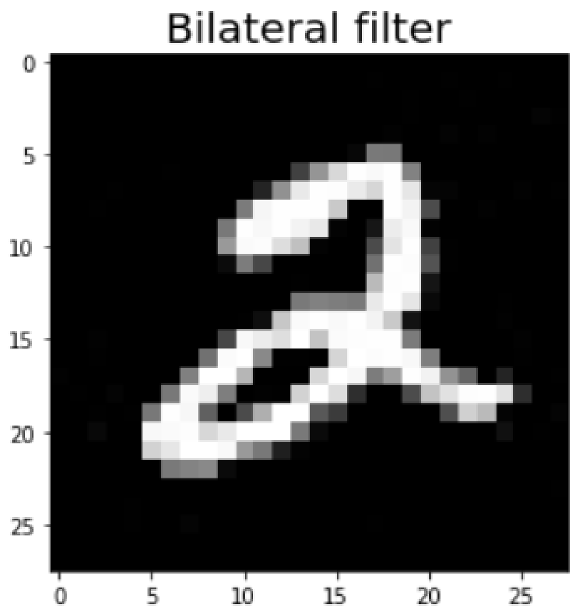
The normalisation term (W_p) is defined as ;

$$W_p = \sum_{x_i \in \Omega} f_r(||I(x_i) - I(\mathrm{x})||) g_s(||x_i - \mathrm{x}||)$$

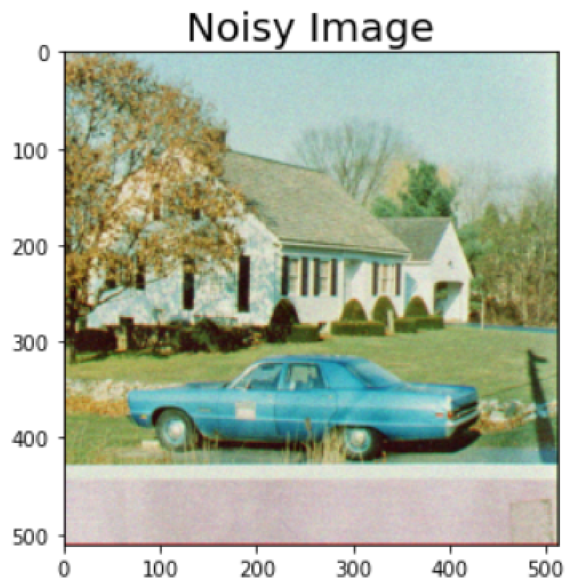
Results obtained by Bilateral filter are:

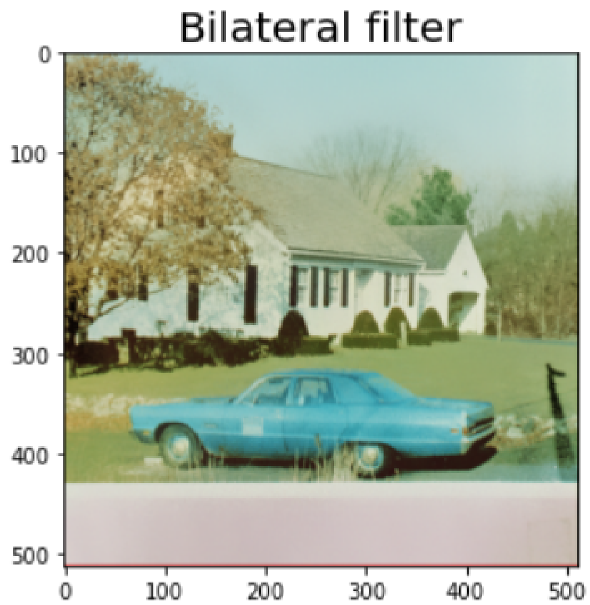
1.) For Grayscale images (MNIST dataset)





2.) For RGB images





2.3) Total Variation filter

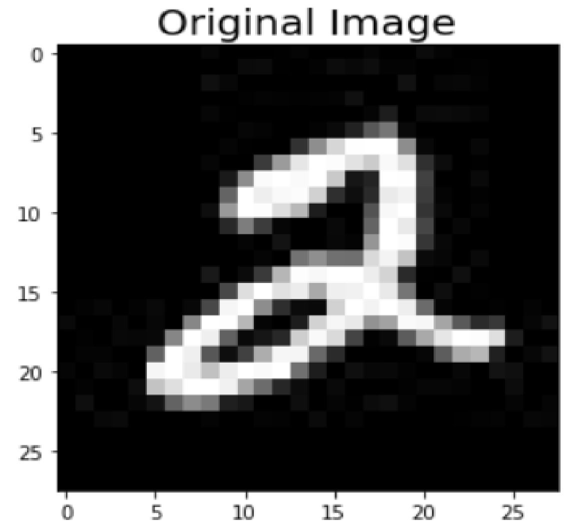
Total variation denoising is a method (filter) for removing noise in images. It is also referred to as total variation regularisation or total variation filtering. It is founded on the idea that signals with excessive and potentially erroneous detail have high total variation, or that the absolute picture gradient integral has a large value. According to this theory, removing unnecessary detail while keeping crucial characteristics like edges can be achieved by decreasing the total variance of the signal, provided that it is closely related to the original signal. Compared to straightforward methods of noise reduction like linear smoothing or median filtering, which lessen noise while also more or less completely removing edges, this method has advantages. Total variation denoising, on the other hand, is a remarkably effective edge-preserving filter, simultaneously maintaining edges and smoothing away noise in flat regions, even at low signal-to-noise ratios.

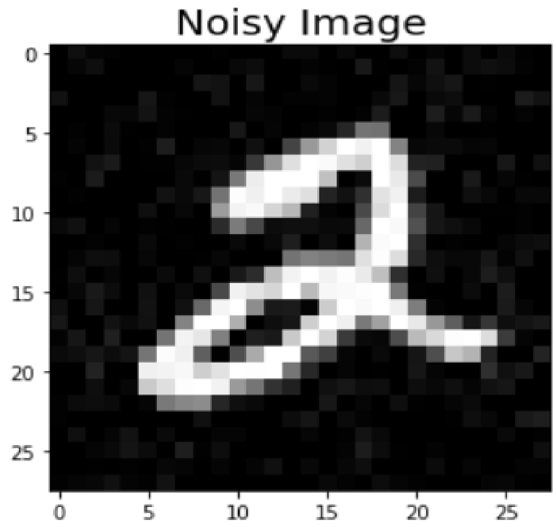
For Digital images (y), the total-variation norm is defined as :

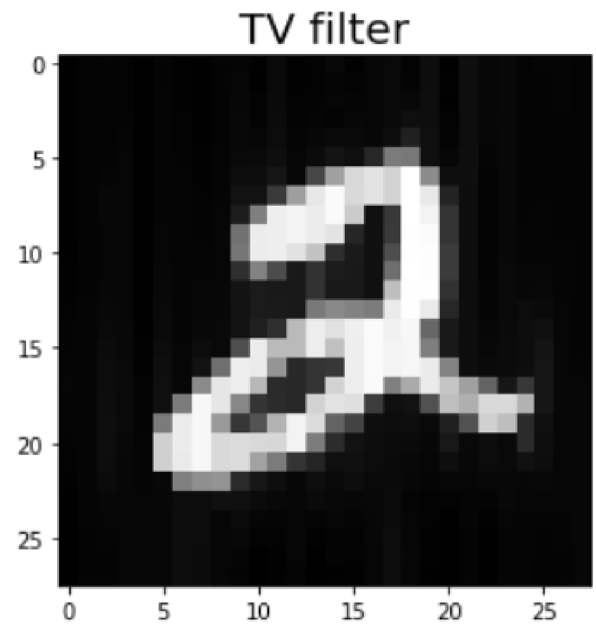
$$V(y) = \sum_{i,j} \sqrt{\left|y_{i+1,j} - y_{i,j}\right|^2 + \left|y_{i,j+1} - y_{i,j}\right|^2}$$

Results obtained by Total variation filter are:

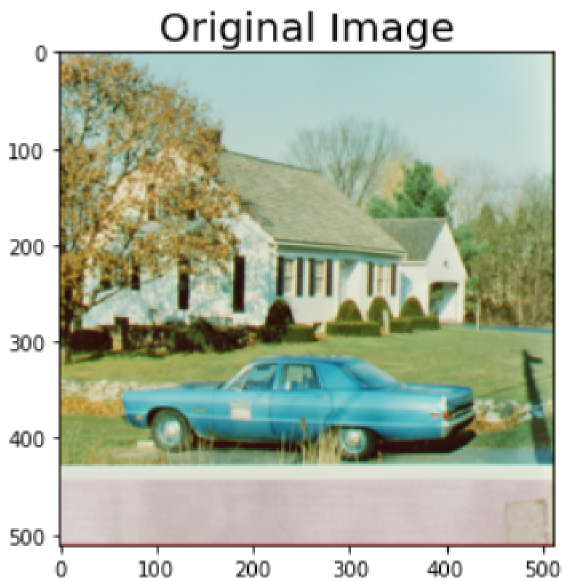
1.) For Grayscale images (MNIST dataset)

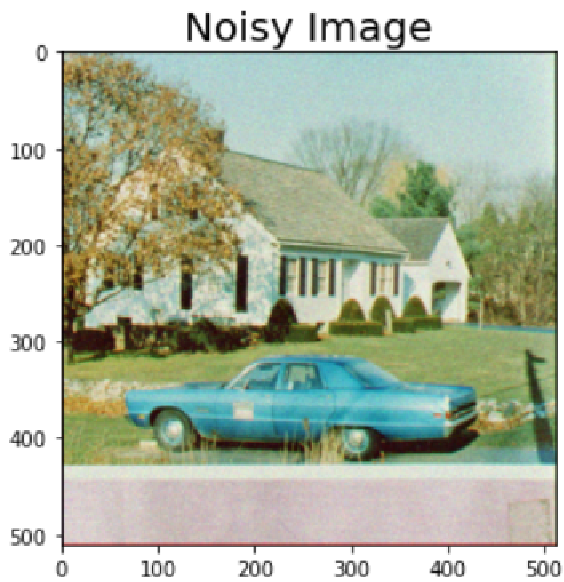


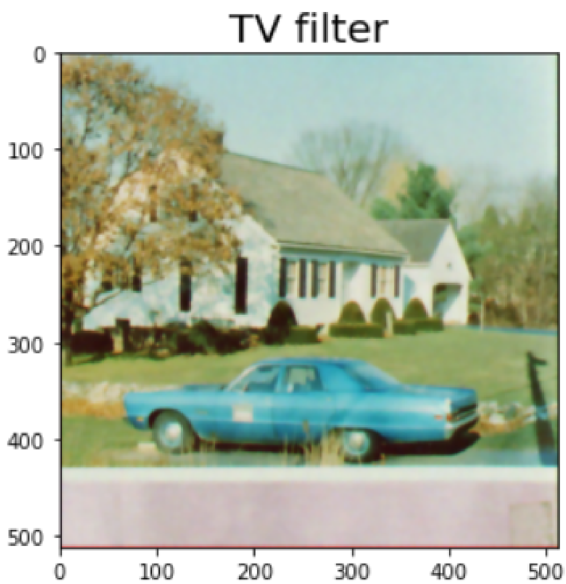




2.) For RGB images





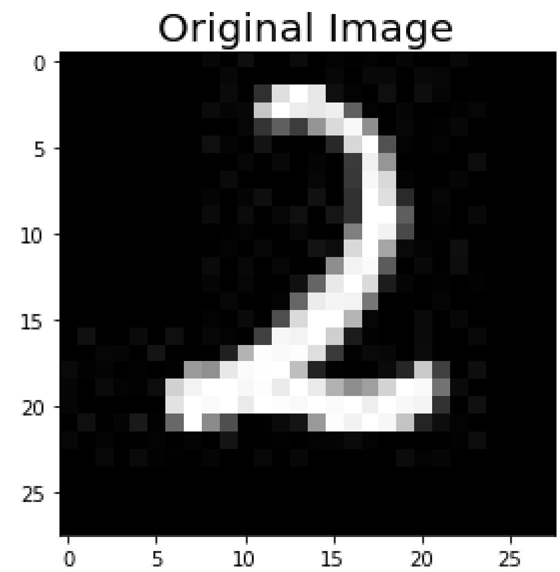


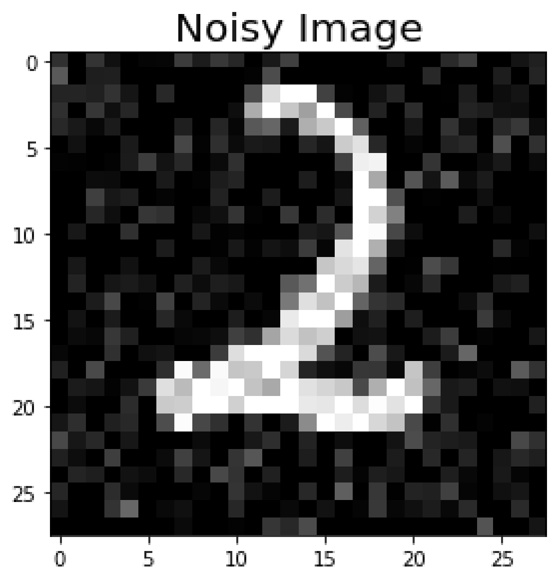
CHAPTER-4: PERFORMANCE ANALYSIS

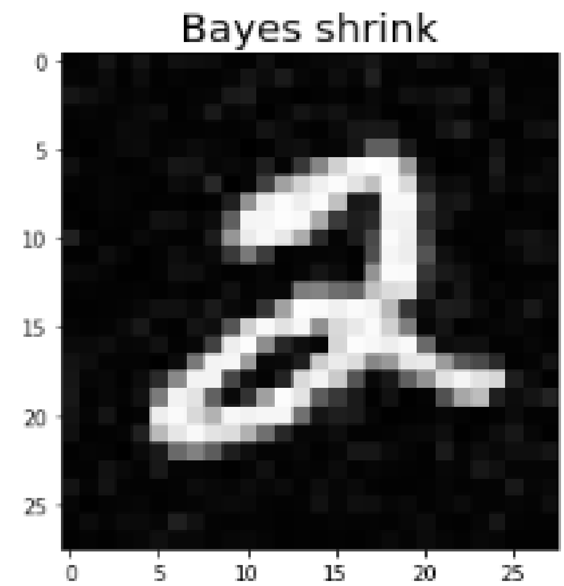
4.1 Analysing the quality between wavelet transform approaches

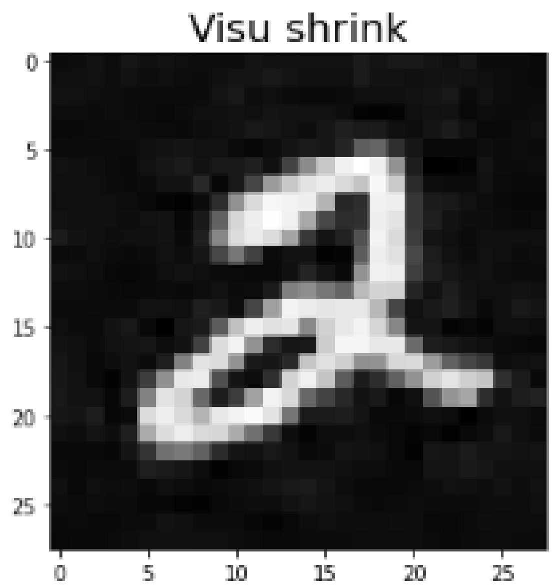
1.) Grayscale images

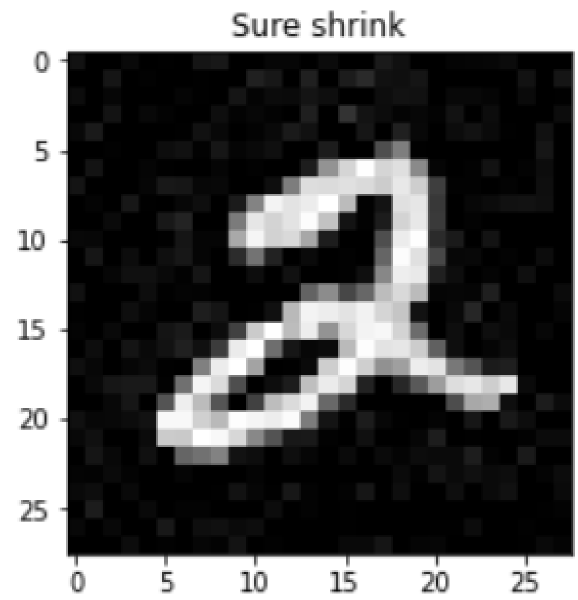
For Soft threshold:











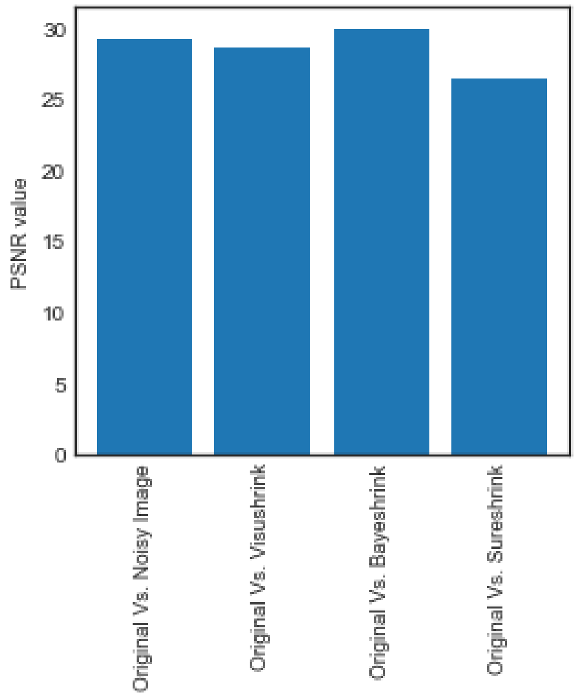
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	28.296	21.303	18.002	15.311	13.821	12.520
Visu shrink	27.037	22.235	19.524	17.615	16.355	14.089
Bayes shrink	29.213	23.372	20.622	18.247	17.043	14.824
Sure shrink	26.816	20.728	17.773	15.804	13.736	12.361

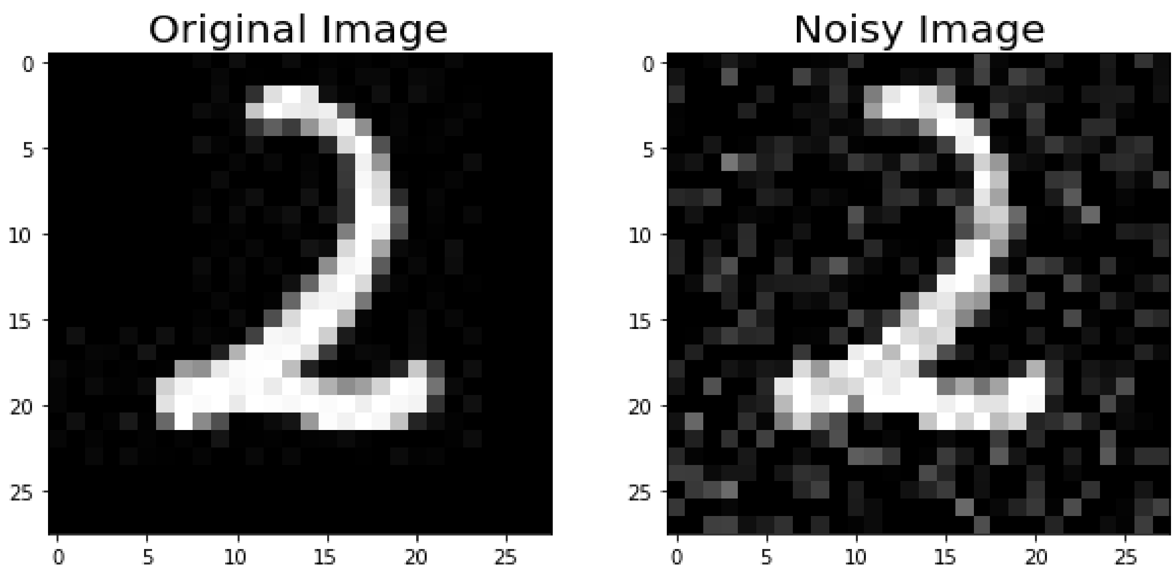
Table 1. PSNR values for grayscale image on soft threshold

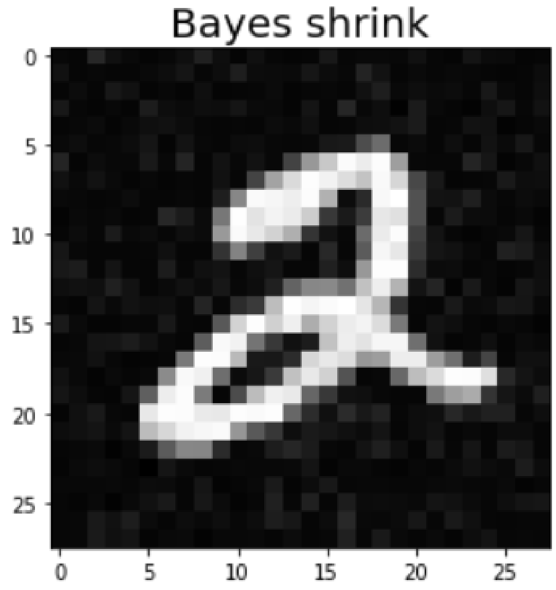
The best quality of image on soft threshold in this table is given by bayes shrink with PSNR value of 29.213 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

Bar graph for best grayscale image quality in soft threshold :



For Hard threshold:




Bayes shrink
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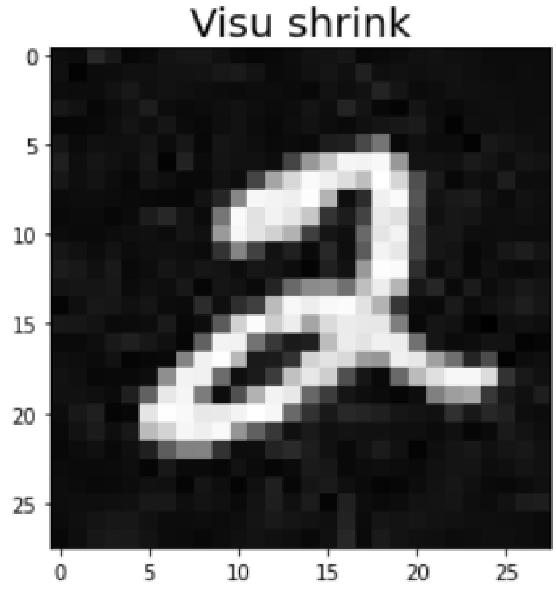
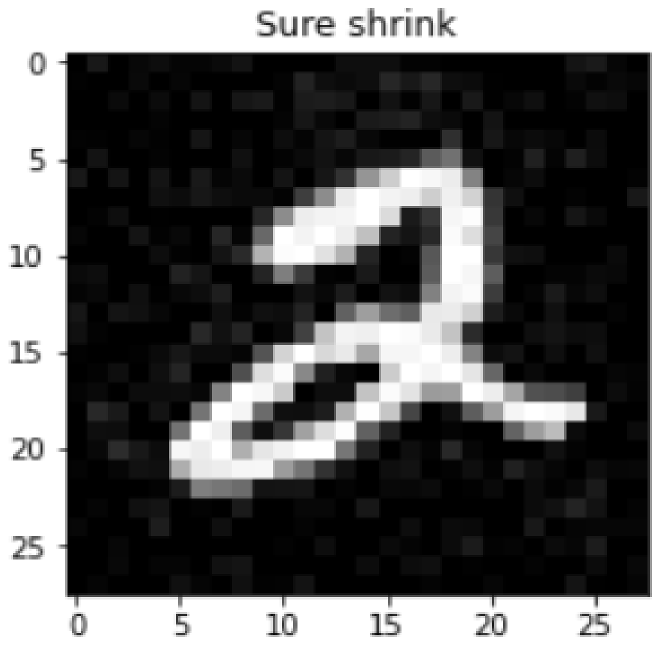
20
25


Visu shrink
0
5
10
15
20
25


Sure shrink
0
5
10
15
20
25

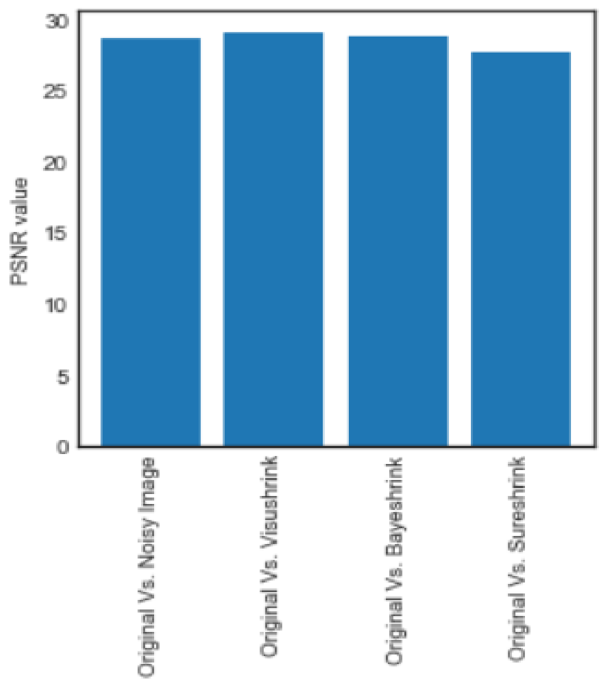
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	28.789	21.931	18.820	15.455	13.913	12.357
Visu shrink	29.127	23.080	19.150	16.911	15.593	13.947
Bayes shrink	28.826	22.997	19.145	17.059	15.215	13.755
Sure shrink	27.937	22.311	18.852	16.581	14.919	13.143

Table 2. PSNR values for grayscale image on hard threshold

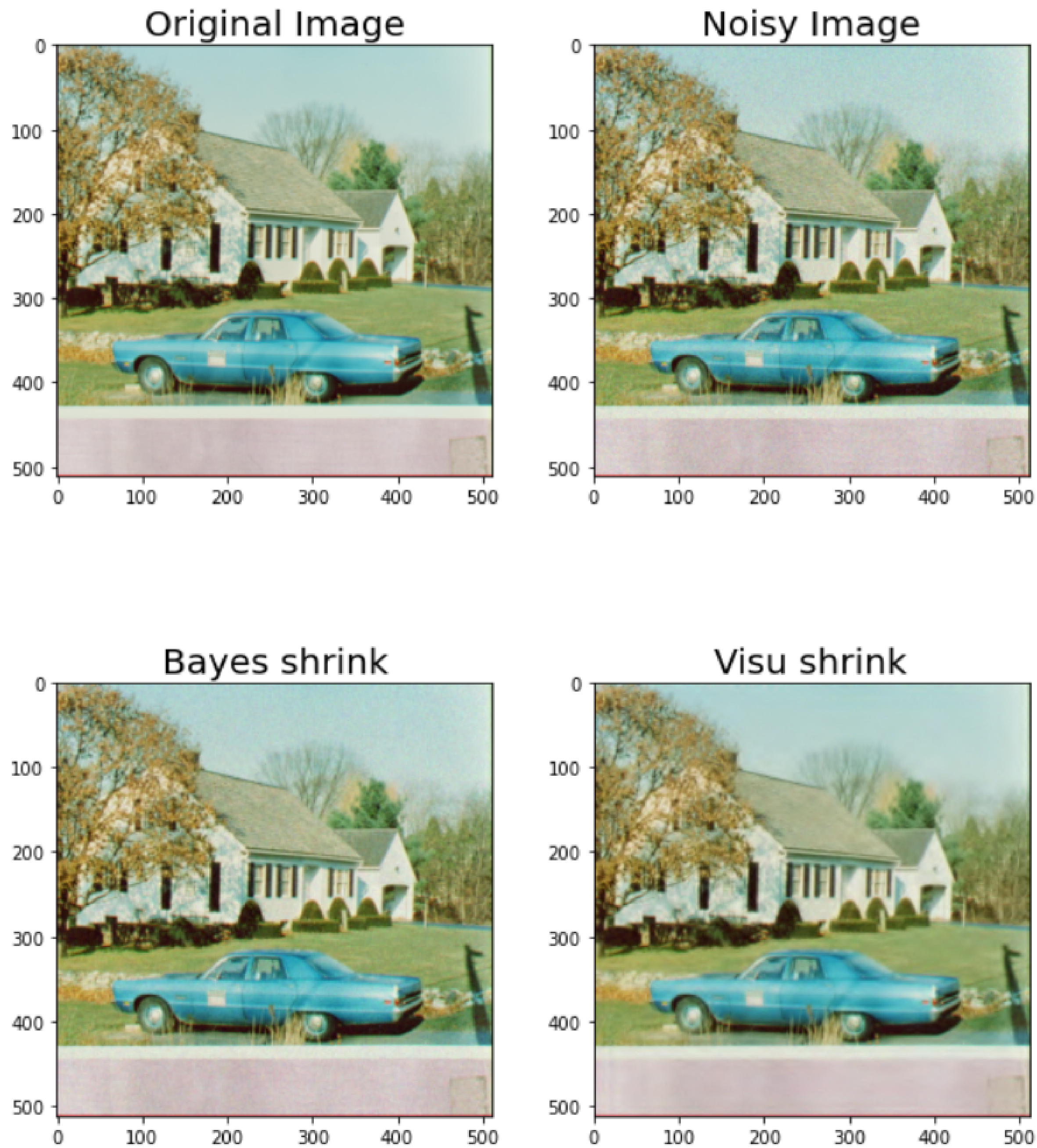
The best quality of image on hard threshold in this table is given by vishu shrink with PSNR value of 29.127 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

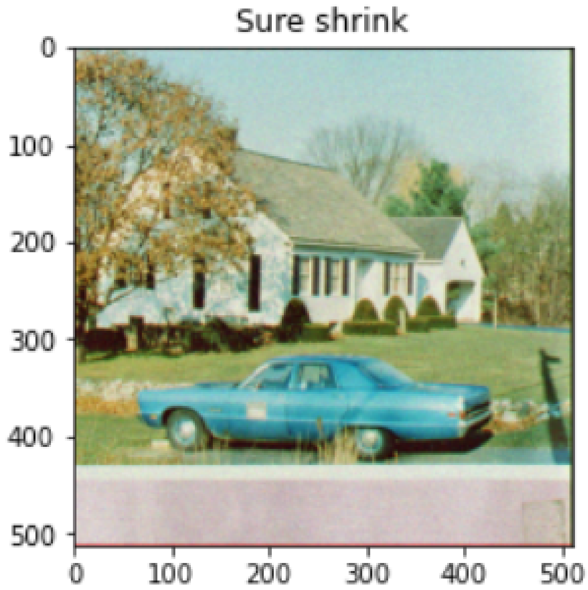
Bar graph for best grayscale image quality in hard threshold :



2.) RGB images

For Soft threshold:





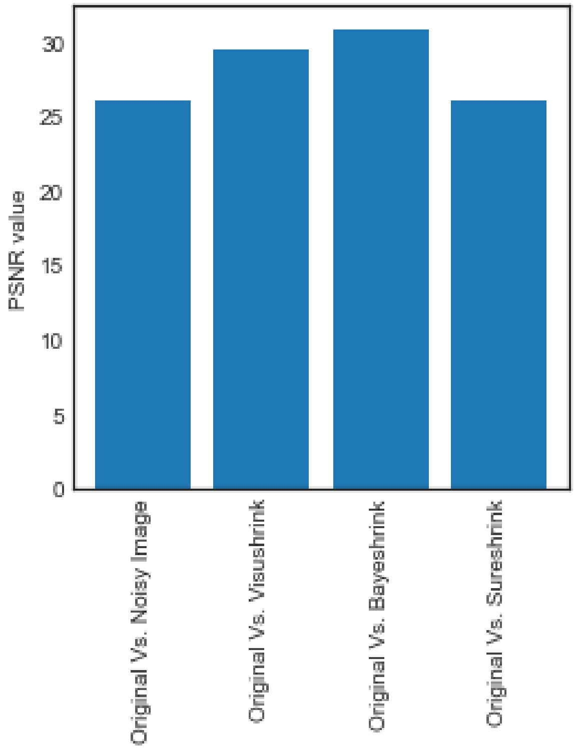
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	26.041	19.165	15.914	13.722	12.149	10.924
Visu shrink	29.459	26.230	24.332	22.851	21.679	20.562
Bayes shrink	30.858	27.419	25.603	24.262	23.199	22.090
Sure shrink	26.043	20.167	16.914	14.745	13.140	11.935

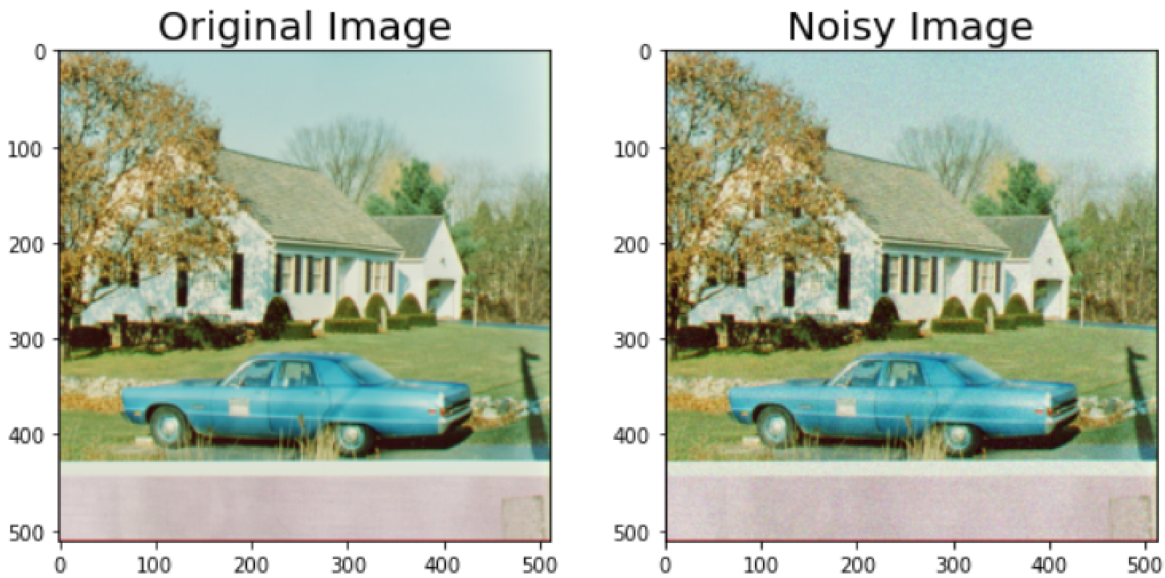
Table 3. PSNR values for RGB image on soft threshold

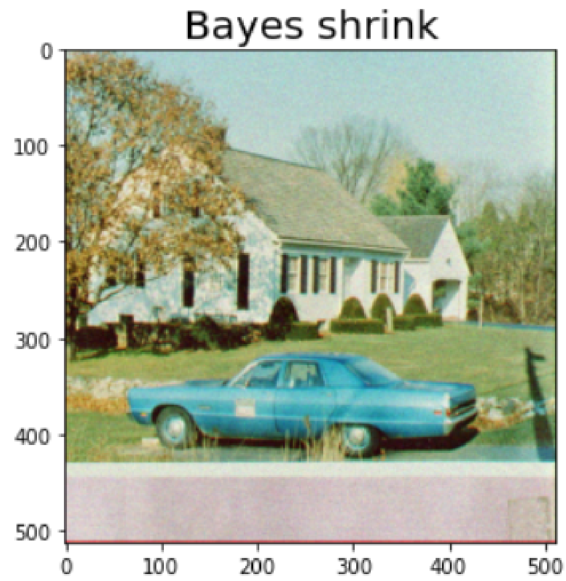
The best quality of image on soft threshold in this table is given by bayes shrink with PSNR value of 30.858 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

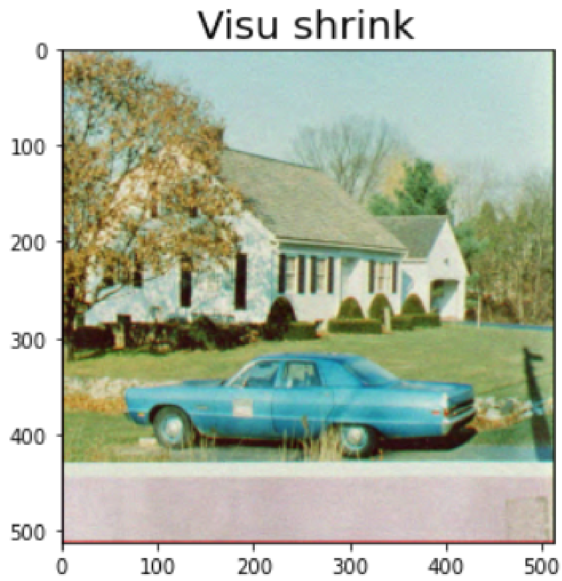
Bar graph for best RGB image quality in soft threshold :

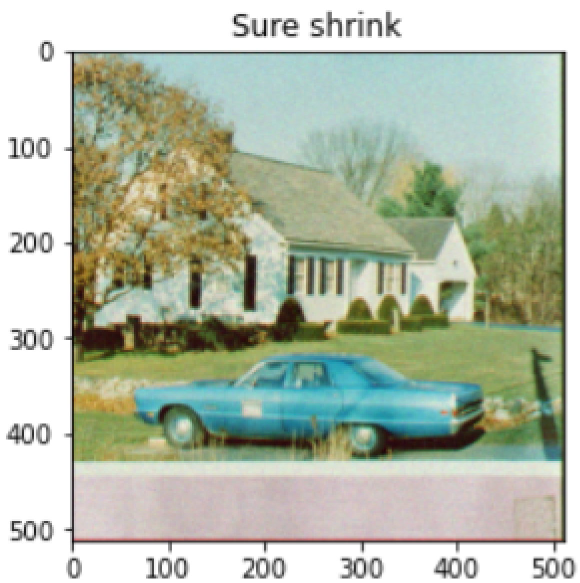


For Hard threshold:




Bayes shrink
0
100
200
300
400
500


Visu shrink
0
100
200
300
400
500


Sure shrink
0
100
200
300
400
500

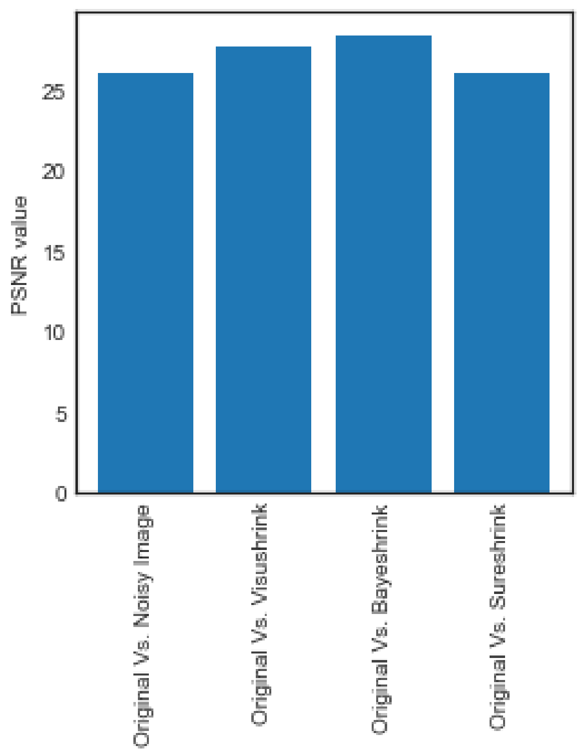
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	26.038	21.176	15.919	13.730	12.157	10.922
Visu shrink	27.703	22.396	19.406	17.318	15.829	14.635
Bayes shrink	28.352	24.570	23.210	22.231	21.281	20.502
Sure shrink	26.041	20.183	16.945	14.745	13.184	11.923

Table 4. PSNR values for RGB image on hard threshold

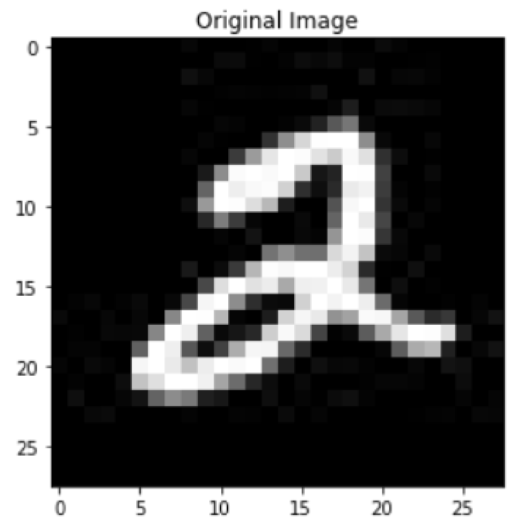
The best quality of image on hard threshold in this table is given by bayes shrink with PSNR value of 28.352 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

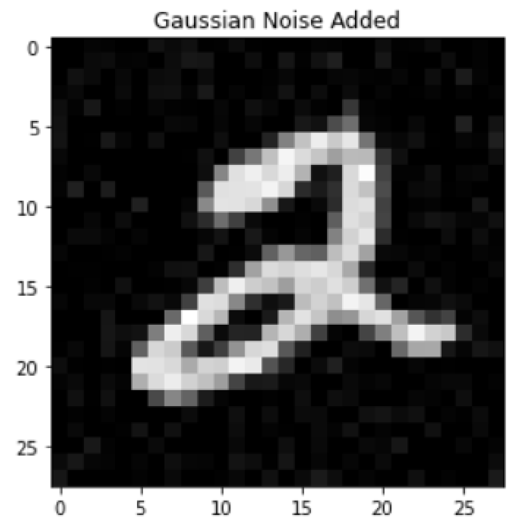
Bar graph for best RGB image quality in hard threshold :

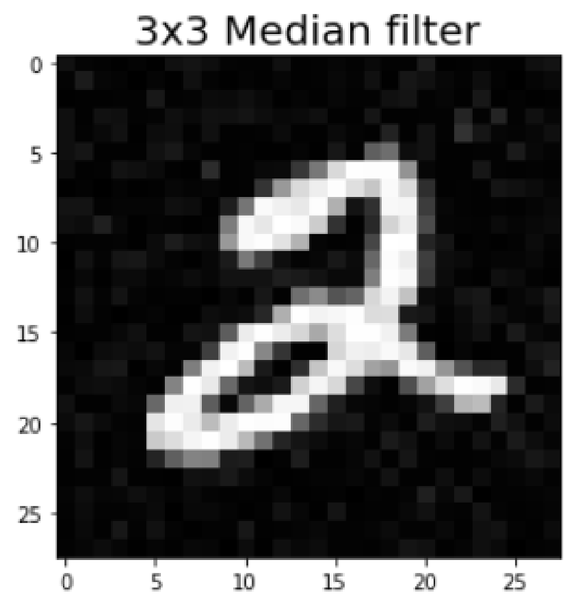


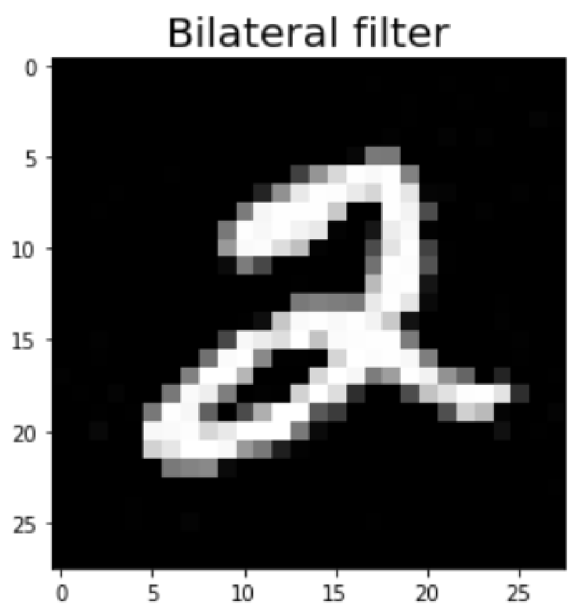
4.2 Analysing the quality between different filters

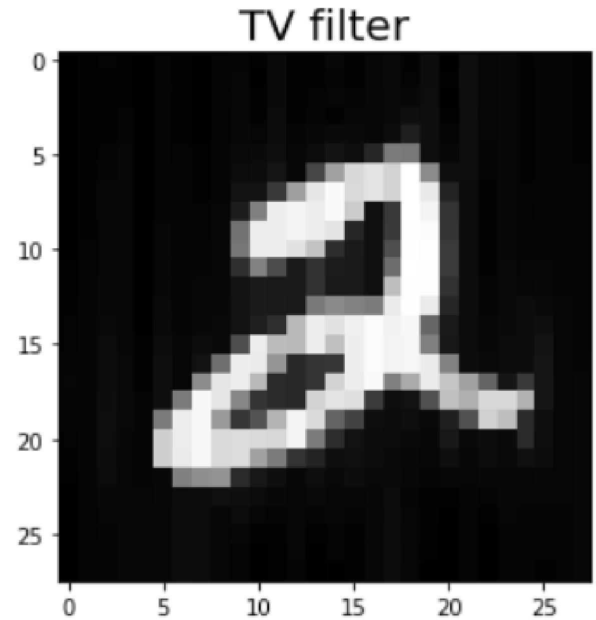
1.) Grayscale images











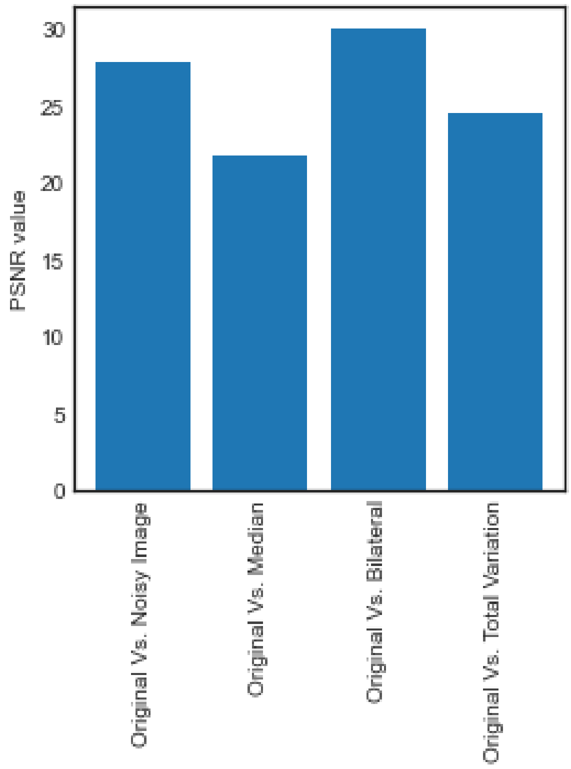
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	28.378	21.877	18.695	15.623	15.063	12.621
Median filter	21.942	20.842	19.543	18.474	17.593	16.826
Bilateral filter	29.695	25.374	19.653	17.200	15.383	13.765
Total Variation filter	25.141	22.653	19.671	18.049	16.600	15.162

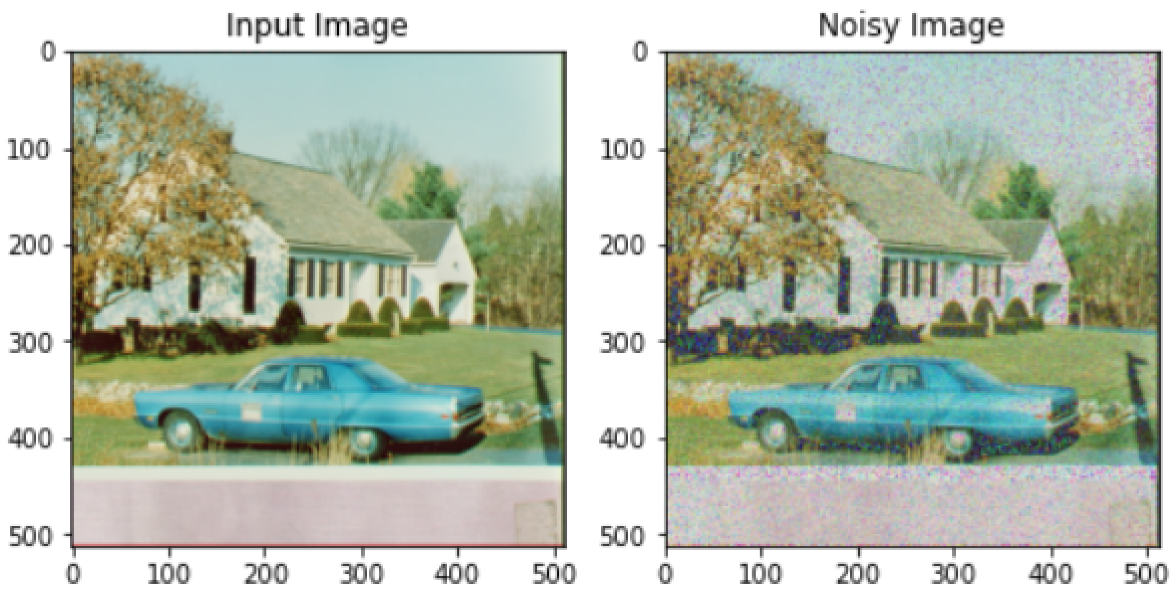
Table 2. PSNR values for grayscale image in filters

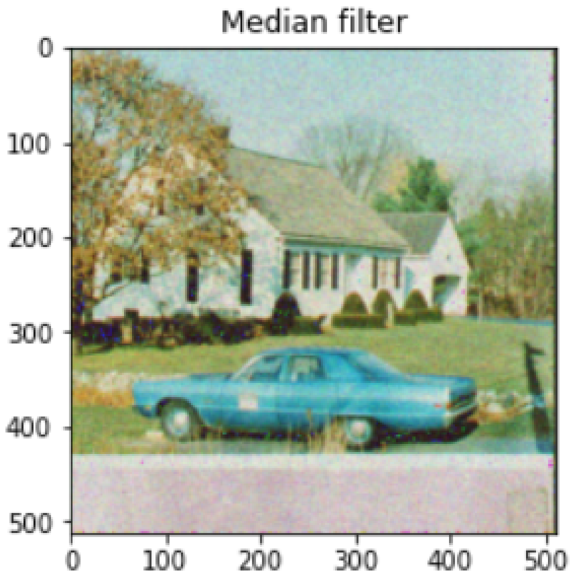
The best quality of grayscale image among filters in this table is given by bilateral filter with PSNR value of 29.695 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

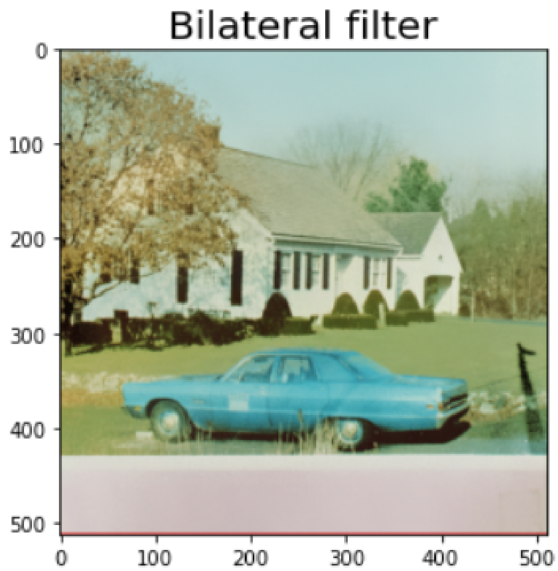
Bar graph for best grayscale image quality:

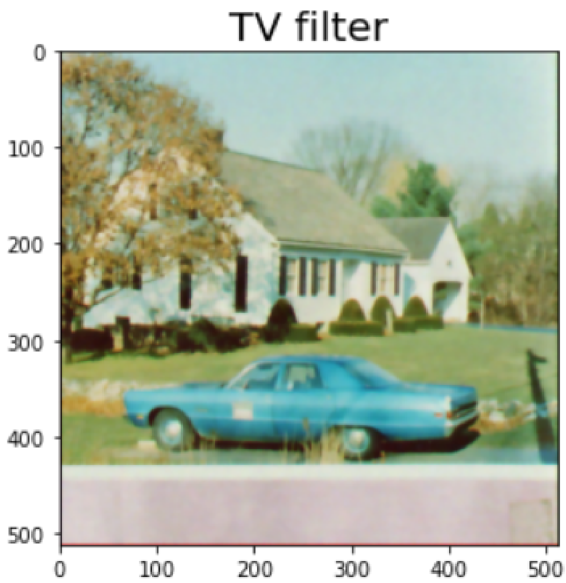


2.) RGB images




Median filter
0
100
200
300
400
500
0
100
200
300
400
500


Bilateral filter
0
100
200
300
400
500
0
100
200
300
400
500


TV filter
0
100
200
300
400
500
0
100
200
300
400
500

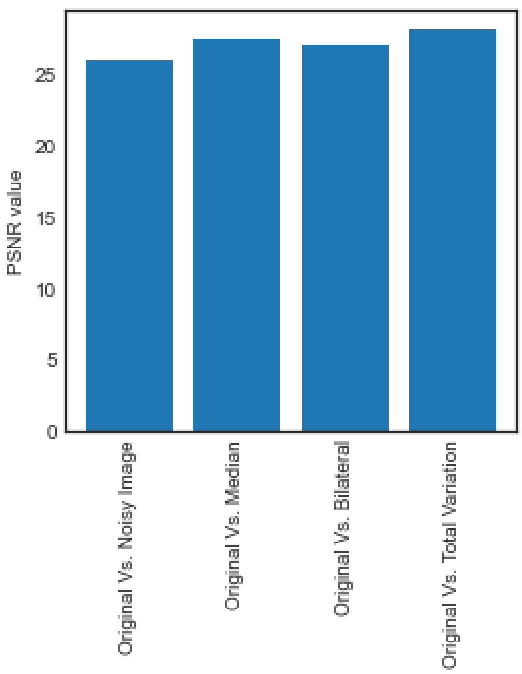
Different values of sigma for PSNR calculation for different methods:

σ	0.05	0.10	0.15	0.20	0.25	0.30
Noisy Image	26.049	21.155	17.901	15.735	14.130	12.917
Median filter	27.611	26.898	25.993	24.941	23.582	22.269
Bilateral filter	27.161	24.660	20.779	17.584	15.208	13.460
Total Variation filter	28.181	27.373	25.828	23.225	20.570	18.476

Table 2. PSNR values for RGB image in filters

The best quality of RGB image among filters in this table is given by Total variation filter with PSNR value of 28.181 on standard deviation of 0.05 because the density of noise here is only 0.05 so the image quality after refinement and reconstruction we get are much clearer than the other method and values of sigma.

Bar graph for best RGB image quality :



CHAPTER-5: CONCLUSIONS

5.1 Conclusions

The results of reconstructing images using various wavelet transform methods and denoising filters demonstrate the versatility of image reconstruction approaches and thresholds. One can use various wavelet transform techniques to restore corrupted images and reduce the impact of noise in them by; bayes shrink, visu shrink and sure shrink. Although there are different approaches to wavelet transforms, they all involve using various thresholds to implement them for the purpose of reducing noise and reconstructing images. Different wavelet transform methods give various results and by using different thresholds, these methods enable thresholds even if the inputs are noisy already, without any noise added. In wavelet transform methods, bayes shrink is the most reliable than any other method and it also gains a greater understanding of the features in the input than any other typical method. Its PSNR value for image quality results high, even for starting threshold value the image quality is much clearer rather than the last threshold value which is high for noise addition. But overall bayes shrink method in wavelet transform is better than visu shrink and sure shrink. For our other method, filters used for image denoising results good on both grayscale and coloured images. Different filters are used in our paper are; bilateral filter, median filter and total variation filter. To evaluate the image's quality in filters we have used PSNR values on different values of sigma. In this filter denoising, the bilateral filter gave optimum results in grayscale data than the other filters; median filter and total variation filter. Sidewise, the total variation filter gave optimum results in RGB data than the other filters; median filter and bilateral filter. The PSNR values for images produced by bilateral filter and total variation filter are also high for grayscale images and RGB images, respectively, it results that the quality index of rebuilt images data is good. In summary, the paper's finding is that the use of bayesshrink technique can effectively enhance the quality of noisy images during reconstruction in wavelet transform for any applied thresholds and bilateral filter for grayscale images and total variation filter for RGB images in denoising filters.

5.2 Future Work

For future work, In order to develop additional methods for image reconstruction using wavelet denoising and filter denoising, we can employ various noises in wavelet transform denoising techniques and filter denoising. Applying the approach, a user-friendly design of GUI can be made that would make it more easy to access for users to replicate their noisy photographs and images.

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